ECONOMIC CONDITION, EDUCATION AND BIRTH ORDER EFFECTS ON HEALTH

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Chapter 1

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Chapter 2

Dedication

This dissertation is dedicated to my parents, my wife and my lovely daughter.

Chapter 3

Abstract

In the first chapter, we estimate the impact of the Great Recession of 2007-2009 on health outcomes in the United States. We show that a one percentage point increase in the unemployment rate resulted in a 7.8-8.8 percent increase in reports of poor health. Mental health was also adversely impacted and reports of chronic drinking increased. These effects were concentrated among those with strong labor force attachments. Whites, the less educated, and women were the most impacted demographic groups.

The second chapter studies the causal effects of education on health in China. The Chinese Ministry of Education released the public announcement of re-institution of higher education in 1977, and it marked the end of 11 years of interruption to the formal education system in recent Chinese history. I use the 1977 Resuming College Entrance Exam Policy as IV and find that education has positive effects on health outcomes in China in general. The results suggest that highly educated people are taller and have stronger grip strength. Men with higher levels of education tend to have less number of IADL, stronger grip strength, and be taller. I also test some possible mechanisms through which education might affect health: cognition and health behaviors. The results do not find clearly education affects health through cognition and health behaviors.

A growing literature in the economics and medical fields explore the birth order effect on health outcomes. However existing literature is limited to a select set of health indicators. The third chapter uses the recently released data – the China Health and Retirement Longitudinal Study (CHARLS), I explore the birth order effect on health outcomes in China. I find some evidence to show that the first born child tends to have better health outcomes relative to those born later

when looking at the overall health status, number of IADL, and cognitive abilities. Moreover, the first born son has some advantage in health compared with the later born sons, while I find little birth order effects for women.

Table of Contents

List of tables

List of figures

Chapter 4

Health and Health Inequality during the Great Recession: Evidence from the PSID*

4.1 Introduction

Recessions are a major source of systematic risk to households. Because they affect large groups of people at once, they are very difficult to insure. Moreover, due to moral hazard problems, public insurance schemes like unemployment insurance only provide limited recourse to the unemployed. As a consequence, recessions can have serious, adverse impacts on household and individual welfare.

One of the more commonly studied of these potential impacts is the effect of recessions on human health. Early work on the topic indicated that poor macroeconomic conditions raised mortality rates substantially (*e.g.* Brenner 1979). However, seminal work by Ruhm (2000) pointed out severe methodological shortcomings in this earlier work and he showed that, once these issues are corrected, mortality rates tend to *decline* during recessions so that mortality rates are actually pro-cyclical in the aggregate data.[1] Improved health-related behaviors due to relaxed time constraints and tightened budget constraints was cited by Ruhm (2000, 2005) as a mechanism driving these results, although subsequent work by Stevens, *et al.* (2015) suggested that higher rates of vehicular accidents and poor nursing home staffing during robust economic times were the primary mechanisms. Notably, more recent work by Ruhm (2015) has shown that mortality rates for many causes of death did not decline during the Great Recession and that mortality due to accidental poisoning actually increased. All of these studies utilize aggregate state-level mortality and unemployment rates and so their unit of analysis is a state/time

[*] This chapter is co-authored with Timothy Halliday and Huixia Wang.

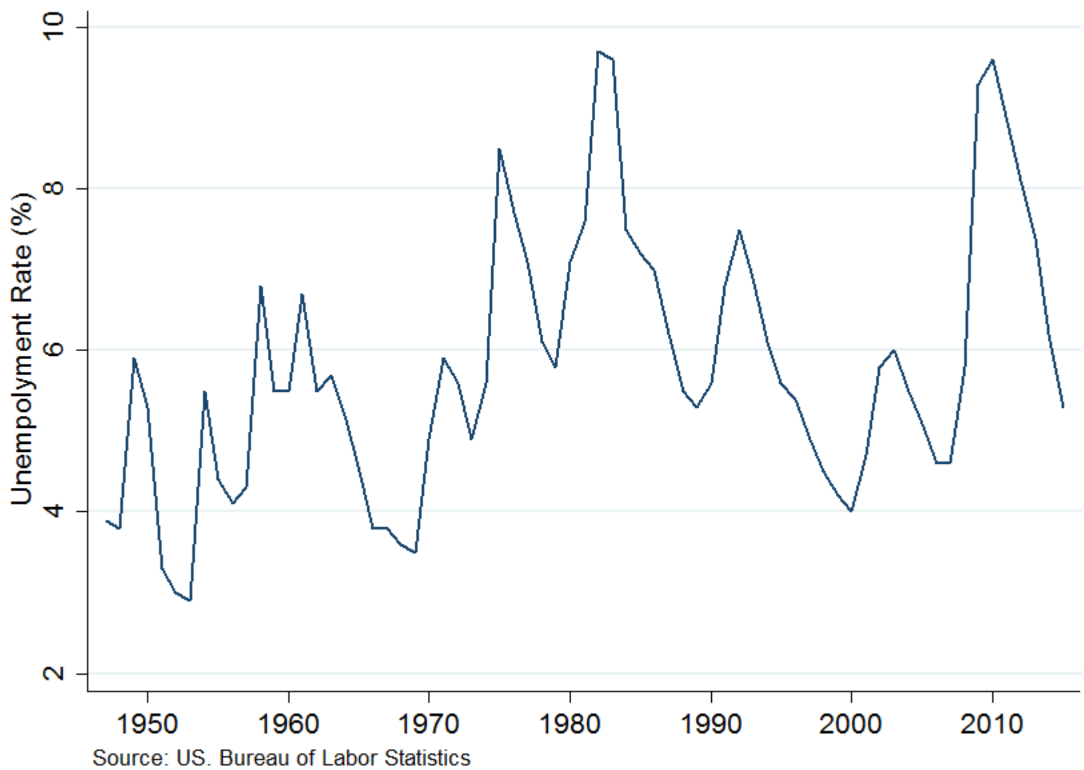
[1] This result has been replicated in other countries such as Canada (Ariizumi and Schirle 2012), France (Buchmueller, *et al*. 2007), OECD countries (Gerdtham and Ruhm 2006), Spain (Tapia Granados 2005), Germany (Neumayer 2004), and Mexico (Gonzalez and Quast 2011).

observation.

On the other hand, studies that are based on individual-level data mostly show that health and health-related behaviors worsen during recessions. For example, Gerdtham and Johannesson (2003, 2005) use micro-data and show that mortality risks increase during recessions for working-aged men. Similar evidence over the period 1984-1993 is provided for the United States by Halliday (2014) who used the Panel Study of Income Dynamics (PSID). Browning and Heinesen (2012) use Danish administrative data and show that involuntary job displacement has large effects on mortality, particularly, from cardiovascular disease which is similar to results in Halliday (2014). This paper builds on earlier work by Browning, Dano, and Heinesen (2006) that does not find any impact of displacements on hospitalization by using more outcomes including mortality, a sample with stronger labor force attachments, as well as a substantially larger data set. In a similar vein to these studies, Jensen and Richter (2003) showed that pensioners who were adversely affected by a large-scale macroeconomic crisis in Russia in 1996 were 5 percent more likely to die within two years of the crisis. Related, Charles and DeCicca (2008) use the National Health Interview Survey (NHIS) and MSA-level unemployment rates to show that increases in the unemployment rate were accompanied by worse mental health and increases in obesity. Hence, while the macro-based studies tend to be somewhat conflicted, the micro-based studies indicate that the uninsured risks posed by recessions have real, adverse impacts on human health. That said there are some micro-based studies that show that health improves during recession *e.g.* Ruhm (2003) who uses a sample from the National Health Interview Survey (NHIS) from 1972-1981.

In this study, we consider how the Great Recession impacted the health of Americans. Specifically, we ask three questions. First, did the Great Recession impact health in the United States? Second, how did it impact health? Third, who did it impact?

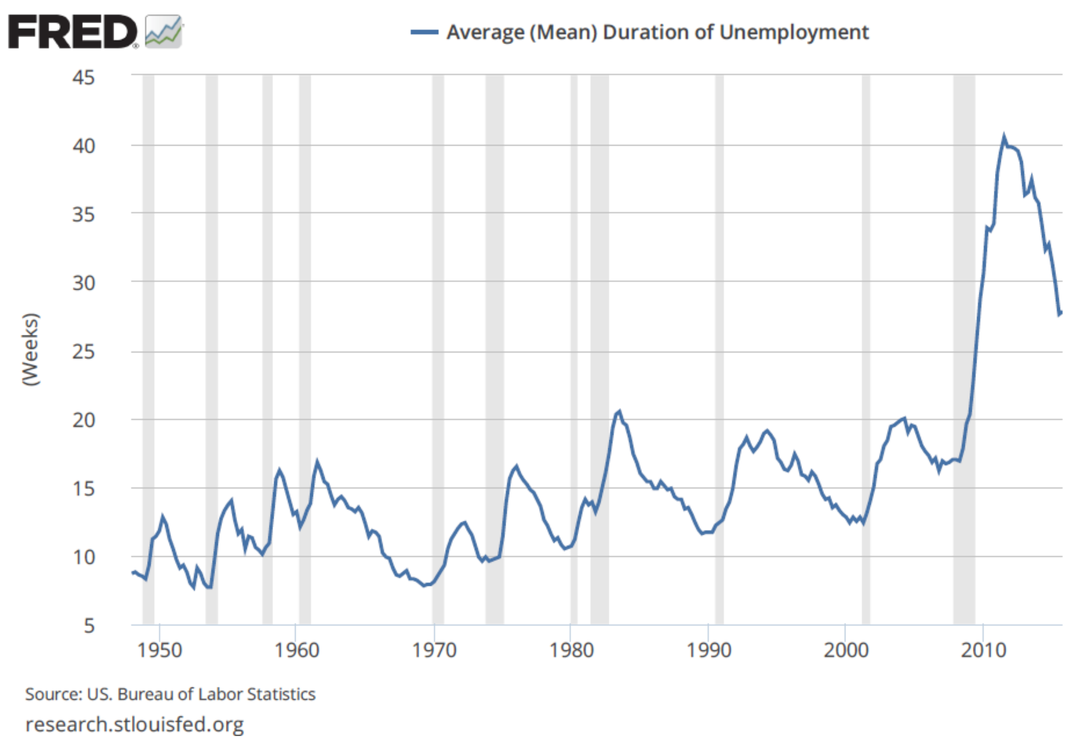
Figure 4.1: Total Unemployment Rate in Each Recession since Postwar



The Great Recession is an important episode to study since this recession was the deepest and longest recession during the post-war period. In fact, Farber (2015) estimates that, over this period, one in six workers lost their job at least once. From trough to peak, the unemployment rate increased from 4.6 to 9.3 percent which is the largest increase during the post-war period. To illustrate, we present Figure 4.1 which shows the unemployment rate during this period. This figure clearly indicates that the recession of 2007-2009 was the most severe. In addition, as shown in Figure 4.2, unemployment duration during the most recent recession was also, by far, the longest of any recession since World War II peaking at just over 40 weeks.

One recent study that considers the health impact of the Great Recession is Tekin, et al. (2013).[2] They use the Behavioral Risk Factor Surveillance System (BRFSS) and find little impact of the Great Recession on health outcomes using state-level unemployment rates. Our study offers two innovations upon their study.

Figure 4.2: Unemployment Duration since Postwar



First, because we employ panel data from the PSID, we have a reliably consistent sample across years and are not subject to the notoriously high non-response rates in many epidemiological surveillance data sources. For example, during the 2000's, the NHIS had a non-response rate over 10 percent (p. 44, Massey and Tourangeau 2012) and the BRFSS had a non-response rate approaching 50 percent during the same period (p. 188, Groves, *et al.* 2009). If the non-

[2] In a similar study, Pabilonia (2015) uses at the Youth Risk Behavior Survey and the American Time Use Survey with a similar research design to investigate the impact of the Great Recession on teenagers' risky behaviors.

response in these surveys is in any way correlated with the business cycles or employment status, then researchers employing these data sources will have biased results.

The second advantage of our study is that we are able to employ more granular information on economic conditions at the county level using the PSID's geocode file. This provides us with a more detailed portrait of the economic conditions that an individual faces. It also provides us with more variation in our right hand side variables which increases the precision of our estimates and, hence, the power of our study.

There are also some other studies that have investigated the impact of the Great Recession on inputs to health, particularly, illicit drug use. For example, Carpenter, *et al.* (2016) look at the impact of the business cycle over the period 2002-2013 on illicit drug use in the United States and find that there is strong evidence that economic downturns lead to increases in the use of prescription pain relievers. This result is consistent with findings in Ruhm (2015) who showed that mortality due to accidental poisoning in the United States increased during the Great Recession. Related to this, Bassols*, et al.* (2016) showed that the Great Recession increased legal and illegal drug use in Spain. Finally, Asgeirsdottir, *et al.* (2012) showed that the 2008 economic crisis in Iceland reduced consumption of health compromising goods.

The findings of our study are as follows. First, there is very strong evidence that the Great Recession impacted the health of working-age Americans. Using a common omnibus measure of health status, self-reported health status, we show that a one percentage point increase in the unemployment rate resulted in a 7.8-8.8 percent increase in reports of fair or poor health status. This finding is robust to a number of tests. These effects were not present in a sample of older people with weaker labor force attachments. Second, the Great Recession adversely impacted mental health and increased drinking, although these effects were weaker than the impact on self-rated health. Third, we detect the strongest impacts on white Americans and those with at most 12 years of schooling. In addition, women were impacted more than men. In this sense our results are consistent with important findings by Case and Deaton (2015) who show that mortality rates of whites with less education have increased during the past 15 years.

The balance of this paper is organized as follows. In the next section, we discuss some avenues through which the macro-economy can affect health. After that, we discuss our data. After that, we describe our empirical methods. We then present our findings. Finally, we conclude.

4.2 Mechanisms

Theoretically, the impact of recessions on health and health-related behavior is ambiguous. This is clearly borne out in the empirical evidence as discussed above. On the whole, the health-promoting effects of recessions will happen via time investment in health and reduced consumption of vices provided that they are normal goods. On the other hand, the harmful effects of recessions will happen through increased consumption of vices if they are inferior goods or increased stress levels.

Health-promoting Effects

These effects have been discussed by many including Ruhm (2000). Essentially, recessions will reduce the opportunity cost of time and incomes. As a consequence, time investment in health will increase and consumption of vices that are also normal goods will decline. Ruhm (2005) does provide evidence for both of these channels using the BRFSS. Evidence for reduced consumption of alcohol and other potentially harmful goods is also provided by Asgeirsdottir, *et al.* (2012) and Cotti, *et al*. (2015). However, it is important to bear in mind that alcohol is a normal good and, so just because some drinking declines during recessions that does not preclude problematic binge drinking from increasing.

Harmful Effects

Recessions may damage health via two channels. First, if some vices are inferior goods, then consumption of them will increase. Moreover, although it may be the case that a good such as alcohol is normal (*e.g.* Cotti, *et al*. (2015)), excessive use of it might be an inferior good if it is used a coping mechanism during stressful times (*e.g.* Dee (2001), Davalos, *et al.* (2012)). A similar argument can be made for obesity since food can also provide comfort during stressful times. Second and related, the stress associated with job loss or the threat of it may, by itself, be a risk factor for a number of ailments which could, thus, lead to a deterioration of health status.

4.3 Data

We utilize data from the PSID which is a national longitudinal study that collects individual-specific information on health, demographic, and socioeconomic outcomes that is run by the University of Michigan. The PSID began in 1968 with interviews of about 5000 families and has continued to interview their descendants since then. To obtain county-specific information, we use the county identifier or the geocode file from the PSID.[3] We utilize the 2003, 2005, 2007, 2009, 2011 and 2013 waves. The 2003 and 2005 waves correspond to the pre-recession period; the 2007 and 2009 waves correspond to the recession period; and the 2011 and 2013 waves correspond to the recovery period. Because only heads of household and their spouses were asked the health-related questions in the survey, we limit our sample to them. We employ regional economic indicators from the Local Area Unemployment Statistics (LAUS) of the Bureau of Labor Statistics (BLS) which were then merged into the PSID for each year using the PSID's geocode file.

For most of the estimations, we restrict the sample to people with strong labor force attachments which we essentially define to be people between ages 25 and 55 and in the labor force. Sample sizes by year for the 25-55 sample are reported in Table A.1. Specifically, we restrict

[3] See http://simba.isr.umich.edu/restricted/ProcessReq.aspx for details.

the 25-55 aged sample by dropping people who reported being out of the labor force, retired and disabled people, students, and housewives. We also present some estimates for people age 65 or older. The idea of using this sample is that this sub-sample has weaker labor force attachments and so if the impact of the recession on health is operating through the labor market then we should see attenuated effects in this population. In addition, because the goal of this exercise is to see if the recession impacted people with weak labor force attachments, we included retired and disabled people, students (to the extent that there are full-time students older than 65), and housewives, as well as people who reported being out of the labor force.

Descriptive statistics for our sample are reported in Table 4.1. The data can be categorized under the rubrics: economic conditions, health outcomes, and demographic controls. The demographic variables are fairly self-explanatory and are listed in the bottom portion of the table.

Health Outcomes

The health outcomes that we consider are drinking, mental health, self-reported health status (SRHS), and obesity. The drinking variable that we use is an indicator for chronic drinking which we define to be drinking several times per week or every day. We use the *K6 Non-specific Psychological Distress* scale as an indicator for mental health which was also used by Charles and DeCicca (2008). The K6 index is based on six questions designed to measure different markers of psychological distress including reports of feelings of effortlessness, hopelessness, restlessness, sadness, and worthlessness during the past 30 days. The K6 distress scale is a weighted sum of these six outcomes. Kessler, *et al.* (2003) has shown that the K6 scale is at least as effective as a number of other depression scales in predicting serious mental health problems. Next, SRHS is a categorical variable that takes on integer values between one and five where one is excellent and five is poor. We transform the SRHS variable into a binary variable that we call poor health when SRHS equal to four or five. Halliday (2014) has shown that SRHS is strongly predictive of mortality in the PSID. Finally, obesity is an indicator for body mass index exceeding 30 which is the standard definition from the Centers for Disease

Table 4.1: Descriptive Statistics

	Age 25 - 55			Age 65 +		
	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Economic Conditions						
County Employment to Population Ratio	43280	0.56	0.09	9185	0.56	0.09
State Employment to Population Ratio	43280	0.60	0.04	9185	0.59	0.04
County Unemployment Rate(%)	43240	6.95	2.75	9177	7.04	2.64
State Unemployment Rate (%)	43280	6.88	2.20	9185	6.99	2.18
Health Outcomes						
Chronic Drinking	24311	0.25	0.43	3360	0.31	0.46
K6 Index	35739	2.98	3.50	7138	2.60	3.57
Poor Health	42964	0.09	0.28	9060	0.32	0.47
Obesity	41903	0.26	0.44	8847	0.22	0.42
Demographic Controls						
Age	43280	40.88	8.84	9176	75.25	7.60
Sex	43280	0.52	0.50	9185	0.43	0.50
Married	43275	0.67	0.47	9185	0.54	0.50
Never married	43275	0.16	0.37	9185	0.02	0.15
Widowed	43275	0.01	0.10	9185	0.33	0.47
Divorced	43275	0.13	0.34	9185	0.10	0.30
Less than High School	41205	0.07	0.26	8635	0.18	0.38
High School Graduated	41205	0.32	0.47	8635	0.40	0.49
College	41205	0.61	0.49	8635	0.42	0.49
White	42608	0.80	0.40	9030	0.87	0.33
Black	42608	0.13	0.33	9030	0.08	0.27

Control and Prevention.

Economic Indicators

We employ data on regional unemployment rates and employment/population (E/P) ratios. These were obtained from the LAUS of the Bureau of Labor Statistics (BLS) and were merged into the PSID using its geocode file either by county or by state. Note that for the E/P ratios, the employment counts in the numerators come from the LAUS and the population counts in the denominators come from the Surveillance, Epidemiology, and End Results Program (SEER). In total, we had 3218 counties in our data.

In our sample, the average county-level unemployment rate was 6.95 percent with a standard deviation of 2.75. At the state level, the corresponding statistics are 6.88 and 2.20 percent. As indicated by the standard deviations, there is 25 percent more variation at the county level than at the state level. A regression of the county-level unemployment rate onto county fixed effects has an R^2 of 47.55 percent indicating that over half of the variation of the county-level unemployment rate is within counties which is critical for our research design's success.

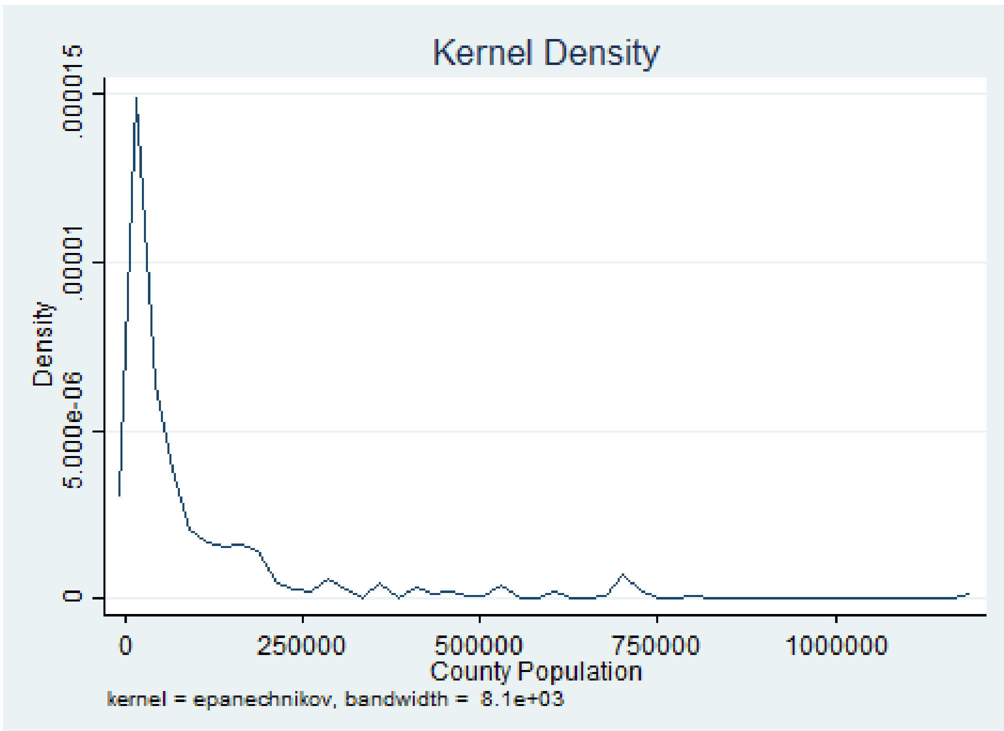
The average county-level E/P ratio was 0.56 with a standard deviation of 0.09. At the state level, the corresponding statistics are 0.60 and 0.04. Accordingly, there is 125 percent more variation at the county level. Note that there is substantially more county-level variation in the E/P ratios than in the unemployment rates. Finally, the R^2 from a regression of the E/P ratio onto a set of county dummies is 41.72 percent once again indicating substantial within county variation in the county-level E/P ratios.

County Population Sizes

In Table A.2, we report some descriptive statistics on county population sizes from the merged

PSID-LAUS-SEER data set. The average county size in the merged data in 99,555, but the median is 35,341 indicating that the distribution of county sizes is skewed to the right. This is reflected in a high standard deviation of 160,419. In Figure 4.3, we present a kernel density estimate of the county sizes also from the merged data set. As suggested by the descriptive statistics, the distribution of county sizes is skewed to the right.

Figure 4.3: Kernel Density of County Populations



4.4 Methodology

To estimate the effect of the Great Recession on health outcomes and health-related behaviors, we employ a linear regression model. If we let *i* denote the individual, *c* the county, *s* the state, and *y* the year, the basic estimation model is:

$$H_{icsy} = \beta_0 + \beta_1 U_{cy} + \beta_2 X_{iy} + \delta_c + \delta_y + \delta_s * t + \varepsilon_{icsy}. \qquad (1)$$

The dependent variable, H_{icsy}, is a health outcome or behavior. The county-specific (or state-specific) unemployment rate (or E/P ratio) in a given year is denoted by U_{cy}. The vector, X_{iy}, contains individual-specific control variables including age, gender, race, marital status, and education. We also include county and year dummies which are denoted by δ_c and δ_y. Finally, we include state-specific time trends which are denoted by $\delta_s * t$. We estimate two different specifications of equation (1) both with and without the state-specific trends which has the advantage of controlling for confounding within state trends but the disadvantage of eliminating potentially meaningful exogenous variation in the county-level economic indicators. All standard errors were clustered on the county level. Finally, we employ the weights provided by the PSID when estimating these models.

Choosing the Economic Indicator

There are two important choices that must be made with respect to the economic indicator on the right-hand side of the estimation equation. The first is whether to focus on state- or county-level indicators. The second is whether to use the E/P ratio or the unemployment rate. We argue that the most appropriate choice in our context is the county-level unemployment rate. Consequently, we mostly focus on these in this paper. However, we do present results at the state and county levels using both indicators.

There are pros and cons of focusing the analysis at the state versus the county level. One advantage of using county-specific indicators is that within states, there can be considerable variation in local economic conditions, particularly, in larger states. As such, using county-specific indicators may do a better job of capturing the macroeconomic circumstances that an individual is facing. In this sense, state-specific indicators can be viewed as error-ridden proxies for the county-specific indicator. On the other hand, Bartick (1996) and Hoynes (2000) point out that there can be considerable amounts of measurement errors in county-specific unemployment rates since these come from surveys and imputations are often used for small counties. Note that this would tend to attenuate estimates based on county-level unemployment rates and, so estimates based on them should be viewed as lower bounds in the presence of classical measurement error. Another argument against using indicators at the county level comes from Lindo (2015). He argues that spillovers in regional economic conditions across counties may result in smaller estimates at the county level.

To shed light on spillovers in our context, we provide a formal test for their presence. To do this, we compute an F-test of the equality of the coefficients on the county and state unemployment rates. First, we estimated two models, one with the county unemployment rate and one with the state unemployment rate, as a system of seemingly unrelated regressions. This allowed us to compute the covariance between the two parameter estimates. Next, using the two estimates from this system, we tested the null that the two parameters from the different equations were equal. This provides a formal test of the presence of spillovers that properly accounts for a positive covariance in the two estimates.

Next, it has been argued that county-level E/P ratios may be preferred to county-level unemployment rates because the former come from administrative data sources, whereas the unemployment rates come from either surveys or imputations (in the case of smaller counties). It is true that the numerators of the E/P ratios come from administrative sources so should be less prone to measurement errors. However, because population counts only come every census year, the denominators do rely on imputations within census years for county and state populations. Moreover, in contrast to the county-level unemployment rates which only use imputations for smaller counties, the E/P ratios necessarily must rely on imputed denominators for all counties and states between census years. So, it is not accurate to say that the E/P ratios are free of measurement errors. Like the regional unemployment rates, they are also measured with errors.

In this paper, we focus on results that employ the county-level unemployment rate for the following reasons. First, as the reader will see, we provide no evidence of spillovers in our context. Second and as we already discussed, there is considerably more variation in the county-level indicators than in the state-level indicators, specifically, 25 percent for the unemployment rate and 125 percent for the E/P ratio. This implies that we will have more precise estimates at the county level than at the state level. Third and related, it is not necessarily the case that there is less measurement error in the E/P ratios. The fact that the county-level E/P ratios have a standard deviation that is 125 percent higher than at the state level is consistent with the notion that there is more measurement error in the county-level E/P ratio than in the unemployment rates.

Controlling for Heterogeneity

Our study also does a comprehensive job of controlling for heterogeneity across local labor markets. Importantly, Tekin, *et al.* (2013) and Ruhm (2005) only control for state fixed effects which only accounts for the state-level and time-invariant confounders. Clearly, the use of state fixed effects may be too coarse since potential confounders such as education and health infrastructure, culture, demographic composition, and weather may vary at a finer geographical level. For example, Asians are about one third of the population in San Francisco whereas they are only 0.4 percent of the population of Sierra County in California. In addition, within states, particularly in the South, some counties are "dry" meaning that alcohol cannot be purchased within them. Simple inclusion of state fixed effects would not account for these within state confounders.

We also adopt a more comprehensive approach to addressing heterogeneity by including individual fixed effects which subsume the county fixed effects. This approach has the advantage of controlling for a greater amount of unobserved confounding variables than the county fixed effects. However, it comes with the cost of wasting important exogenous variation in the data as has been argued by Deaton (1997) and Angrist and Pischke (2008). It is also less efficient and exacerbates the attenuation bias caused by measurement errors (*e.g.* Griliches and Hausman 1986). As such, we view the results with the individual fixed effects as a robustness check for our core results and we primarily focus on the results with the county fixed effects for most of the paper.

4.5 Results

In this section, we answer our three research questions. First, did the Great Recession affect health? Second, how did it affect health? Third, who did it affect?

Did the Great Recession affect health?

To address this question, we estimate equation (1) using poor health as the dependent variable. We begin with the SRHS measure as it is a good omnibus measure of health status that exhibits meaningful time series variation. Moreover, as shown in Halliday (2014), it is highly correlated with mortality in the PSID. The results are reported in Table 4.2a.

Our core results are reported in the first four columns. In the first column where county fixed effects are included, the estimate is 0.008 and is significant at the 1 percent level. This indicates that a one percentage point (PP) increase in the unemployment rate results in a 0.8 PP increase in the probability of reporting poor health. Inclusion of the state-specific trend slightly attenuates the estimate to 0.007 but it is still highly significant. The mean of reports of poor health in our data is 0.09, so these estimates constitute 7.8-8.8 percent increases.

One concern with the estimates with the county fixed effects in the first two columns is that healthier people may selectively migrate out of depressed areas as shown in Halliday (2007). If this were to happen then areas with high unemployment rates would have a less healthy population due to selection as opposed to a structural effect of the macroeconomy on individual health. One way to address this is with the inclusion of individual fixed effects as in columns three and four. Another way to address this is to re-estimate the models in the first two columns

Table 4.2a: Poor Health (SRHS = 4 or 5), Ages 25-55

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Unemployment Rate (County)	0.008*** (0.002)	0.007*** (0.002)	0.007*** (0.002)	0.008*** (0.003)	0.007*** (0.002)	0.007*** (0.003)						
Unemployment Rate (State)							0.010*** (0.002)	0.009*** (0.003)				
Emp/Pop Ratio (County)									0.028 (0.030)	0.004 (0.030)		
Emp/Pop Ratio (State)											-0.575** (0.212)	-0.433 (0.289)
F-Test							(1)=(7) [0.984]	(2)=(8) [0.995]			(9)=(11) [0.976]	(10)=(12) [0.995]
County FE	X	X			X	X	X	X	X	X	X	X
Individual FE			X	X								
State-specific Linear Trends		X		X		X		X		X		X
Non-mover Sample					X	X						
NT	40,721	40,721	40,721	40,721	25,142	25,142	40,761	40,761	40,761	40,761	40,761	40,761

* sig. at 10% level   ** sig. at 5% level   *** sig. at 1% level
Notes: All standard errors are clustered at the county level and are reported in parentheses. All specifications control for the demographic variables listed in Table 4.1. We report the p-value for the F-tests in brackets.

for a subsample of people who do not move counties while in the sample. These results are reported in columns three through six. All four estimates estimates are between 0.007 and 0.008 and remain significant at the 1 percent level. This indicates that selective migration is not driving our results.

In columns seven and eight, we use the state unemployment rate instead of the county unemployment rate. The estimates are 0.010 and 0.009 without and with state-specific trends. While this is larger than the analogous estimates in the first two columns, the magnitude of the difference is not as large as what was found in Lindo (2015). The p-values on an F-test of the equality of the coefficients on the county and state unemployment rates are close to unity indicating that we cannot reject the null that the two estimates are the same. This casts doubt that there are spillover effects in our context.

We also report estimates based on county and state level E/P ratios in the final four columns. Of these four estimates, only the estimate using the state-level ratio in column 11 is significant. It is interesting to note that the estimates that use the state E/P ratios are substantially larger than those that use the county-level ratios. One possible reason is that the estimated county populations in the denominators are more inaccurate than the state population estimates which could result in more measurement error at the county level. In addition, none of the corresponding estimates with the other health outcomes produced a significant estimate.[4] Given that most of our effects appear to be operating through the county-level unemployment rate, we will focus on it for the duration of the paper.

Finally, we estimate the same models as in Table 4.2a except that we drop observations that reside in small counties. Specifically, we estimate the models for people living in counties with populations above the 15th percentile in the merged data. We do this since the BLS imputed

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4 These results are available upon request.

Table 4.2b: Poor Health (SRHS = 4 or 5), Ages 25-55, Dropping Small Counties (Bottom 15%)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Unemployment Rate (County)	0.008*** (0.002)	0.007*** (0.002)	0.008*** (0.003)	0.008*** (0.003)	0.009*** (0.003)	0.007*** (0.003)						
Unemployment Rate (State)							0.010*** (0.003)	0.008*** (0.003)				
Emp/Pop Ratio (County)									0.034 (0.041)	-0.005 (0.045)		
Emp/Pop Ratio (State)											-0.596** (0.254)	-0.659* (0.393)
F-Test							(1)=(7) [0.984]	(2)=(8) [0.995]			(9)=(11) [0.976]	(10)=(12) [0.995]
County FE	X	X			X	X	X	X	X	X	X	X
Individual FE			X	X								
State-specific Linear Trends		X		X		X		X		X		X
Non-mover Sample					X	X						
NT	34,651	34,651	34,651	34,651	17,394	17,394	34,691	34,691	34,691	34,691	34,691	34,691

* sig. at 10% level ** sig. at 5% level *** sig. at 1% level
Notes: Per Table 4,2a.

unemployment rates for smaller counties. In addition, given our discussion about the denominators in the E/P ratios, there may be reasons to believe that measurement errors in these indicators are greater in smaller counties.

The results are reported in Table 4.2b and are basically identical to those in Table 2a except some of the standard errors are slightly larger due to dropping 15 percent of the observations. If measurement errors were more problematic in smaller counties, then we would expect to see larger estimates in this table than in the previous table (provided that we are dealing with well-behaved classical measurement error). That said, this does not mean that measurement errors are not a problem, overall. It just means that they do not appear to be more important in smaller counties than in larger counties.

How did the Great Recession affect health?

Having established that the Great Recession impacted an omnibus health measurement, we now try and understanding how the recession impacted different components of health. To accomplish this, we estimate the model in equation (1) using the K6 index, the chronic drinking indicator, and the obesity indicator as the dependent variables.

The results are reported in Table 4.3. First and consistent with Tefft (2011), we see in the first two columns that mental health as proxied by the K6 scale deteriorated during the Great Recession. The estimates without and with the state-specific trends are significant at the 10 percent level. Note that in columns three and four where we use state-level unemployment rates, both estimates are small in magnitude and not significant, but due to their large standard errors, we cannot reject that these estimates are equal to the estimates at the county level. Moving on to drinking in columns five and six, we see that a one PP increase in the county-level unemployment rate increases the propensity to drink by 0.6-0.8 PP. From Table 4.1, the mean of

Table 4.3: Mental Health, Drinking, and Obesity, Ages 25-55

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	K6 Depression Index				Chronic Drinking				Obesity			
Unemployment Rate (County)	0.053* (0.028)	0.057* (0.030)			0.006* (0.003)	0.008** (0.003)			-0.002 (0.003)	-0.001 (0.003)		
Unemployment Rate (State)			0.042 (0.031)	0.046 (0.039)			0.005 (0.004)	0.009* (0.005)			-0.001 (0.003)	0.001 (0.003)
F-Test			(1)=(3) [0.999]	(2)=(4) [0.999]			(5)=(7) [0.999]	(6)=(8) [0.998]			(9)=(11) [0.999]	(10)=(12) [0.999]
County FE	X	X	X	X	X	X	X	X	X	X	X	X
State-specific Linear Trends		X		X		X		X		X		X
NT	33,937	33,937	33,937	33,937	23,288	23,288	23,307	23,307	39,774	39,774	39,813	39,813

* sig. at 10% level   ** sig. at 5% level   *** sig. at 1% level
Notes: Per Table 4.2a.

this variable is 0.25, so this constitutes a 2.4-3.2 percent increase. The corresponding estimates with the state unemployment rate in columns seven and eight are similar in magnitude, although only the estimate with the state-trends is significant at conventional levels. Once again, we do not find any evidence of spillovers. Finally, we look at obesity in the final four columns and see no evidence of any effects.

Next, in Table 4.4, we estimate our model for our four main outcomes on a sample that is 65 or older that has weak labor force attachments. None of the estimates are significant. Although it is true that due to a smaller sample size, this may be the result of less power. However, it is interesting to note that the magnitudes also tend to be smaller than the corresponding magnitudes in Tables 4.2 and 4.3 for the working age population, so the lack of significance is not only due to higher standard errors. This is suggestive that our effects are operating via the labor market.

Table 4.4: Ages 65 and older

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Poor Health		K6 Index		Chronic Drinking		Obesity	
Unemployment Rate (County)	-0.003 (0.005)	-0.002 (0.005)	0.012 (0.049)	0.022 (0.052)	-0.001 (0.011)	-0.006 (0.012)	-0.003 (0.004)	-0.004 (0.004)
County Fixed Effects	X	X	X	X	X	X	X	X
State-specific Trends		X		X		X		X
NT	8,556	8,556	6,722	6,722	3,212	3,212	8,377	8,377

* sig. at 10% level ** sig. at 5% level *** sig. at 1% level
Notes: Per Table 4.2a.

Who was impacted the most by the Great Recession?

Finally, we investigate how the Great Recession affected different socioeconomic groups. In

Table 4.5: Effects by Race, Ages 25-55

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Blacks							
	Poor Health		K6 Depression Index		Chronic Drinking		Obesity	
Unemployment Rate (County)	0.003	-0.001	-0.047	-0.025	0.012	0.022**	0.013*	0.011
	(0.006)	(0.006)	(0.073)	(0.087)	(0.010)	(0.011)	(0.007)	(0.007)
County Fixed Effects	X	X	X	X	X	X	X	X
State-specific Trends		X		X		X		X
N	12,929	12,929	10,795	10,795	6,404	6,404	12,673	12,673
	Whites							
County Unemployment Rate	0.008***	0.007***	0.061**	0.069**	0.007**	0.009**	-0.005*	-0.003
	(0.002)	(0.002)	(0.030)	(0.033)	(0.004)	(0.004)	(0.003)	(0.003)
County Fixed Effects	X	X	X	X	X	X	X	X
State-specific Trends		X		X		X		X
NT	25,538	25,538	21,238	21,238	15,870	15,870	24,936	24,936

* sig. at 10% level   ** sig. at 5% level   *** sig. at 1% level
Notes: Per Table 4.2a.

Table 4.5, we estimate our models separately for blacks and whites. In Table 4.6, we estimate the model separately for high school and college educated people. Finally, in Table 4.7, we estimate the models separately by gender.

In Table 4.5, we report the results for blacks in the top panel and for whites in the bottom panel. For blacks, we do not see any impacts on poor health or the K6 scale. In contrast, we do see strong evidence of effects on these outcomes for whites. Based on this evidence, the recession had larger effects on whites. Next, looking at drinking, we see tightly estimated and significant effects on drinking behavior for whites. For blacks, the estimates are less tightly estimated and only the estimate with the state-trends is significant in column six. However, the magnitudes are larger for blacks than for whites. Finally, looking at obesity in column seven which excludes the state-trends, there is evidence of impacts on obesity albeit in opposing ways. A one PP increase in the unemployment rate increases the propensity to be obese for blacks by 1.3 PP but *decreases* the propensity for whites by 0.5 PP. However, these results are not robust to the inclusion of state-trends in the final column. Our interpretation of these results is that there is stronger evidence that the recession impacted the health of white Americans than black Americans.

Table 4.6 is analogous to the previous table except that now we stratify by education level. First, we see that none of the estimates are significant for college graduates. Second, we see that, for the high school educated, there are significant impacts on SRHS and drinking when state-trends are included in column six. This table suggests that there is stronger evidence that the recession had larger impacts on the less educated.

Finally, in Table 4.7, we investigate gender differences in the effects of the Great Recession on health. First, we see substantially larger impacts on SRHS for women than for men. The point estimates for women are 0.010 and 0.007 without and with the state-specific trends. Both are

Table 4.6: Effects by Education, Ages 25-55

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High School Education (at most 12 years of schooling)							
	Poor Health		K6 Depression Index		Chronic Drinking		Obesity	
Unemployment Rate (County)	0.008**	0.007*	0.048	0.034	0.006	0.013*	-0.006	-0.006
	(0.004)	(0.004)	(0.041)	(0.045)	(0.006)	(0.007)	(0.005)	(0.005)
County Fixed Effects	X	X	X	X	X	X	X	X
State-specific Trends		X		X		X		X
N	15,977	15,977	13,073	13,073	8,207	8,207	15,649	15,649
	College Graduates							
County Unemployment Rate	0.004	0.002	0.019	0.041	0.008	0.004	-0.002	0.001
	(0.003)	(0.003)	(0.042)	(0.048)	(0.006)	(0.006)	(0.004)	(0.004)
County Fixed Effects	X	X	X	X	X	X	X	X
State-specific Trends		X		X		X		X
NT	12,205	12,205	10,430	10,430	8,115	8,115	11,932	11,932

* sig. at 10% level   ** sig. at 5% level   *** sig. at 1% level
Notes: Per Table 4.2a.

Table 4.7: Effects by Gender, Ages 25-55

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Men							
	Poor Health		K6 Depression Index		Chronic Drinking		Obesity	
Unemployment Rate (County)	0.004	0.005*	0.058*	0.050	0.005	0.008	0.001	0.003
	(0.002)	(0.003)	(0.032)	(0.035)	(0.005)	(0.005)	(0.003)	(0.004)
County Fixed Effects	X	X	X	X	X	X	X	X
State-specific Trends		X		X		X		X
N	20,560	20,560	17,093	17,093	12,673	12,673	20,338	20,338
	Women							
County Unemployment Rate	0.010***	0.007**	0.043	0.052	0.008*	0.008*	-0.008*	-0.007*
	(0.003)	(0.003)	(0.040)	(0.044)	(0.004)	(0.004)	(0.004)	(0.004)
County Fixed Effects	X	X	X	X	X	X	X	X
State-specific Trends		X		X		X		X
NT	20,161	20,161	16,844	16,844	10,615	10,615	19,436	19,436

* sig. at 10% level   ** sig. at 5% level   *** sig. at 1% level
Notes: Per Table 4.2a.

significant at the 1 percent level. The corresponding estimates for men are 0.004 and 0.005 and neither is tightly estimated. Similarly, we see that a 1 PP increase in the unemployment rate increase the probability of chronic drinking for women by 0.8 PP and both estimates are significant at the 10 percent level. The corresponding estimates for men are 0.005 and 0.008 but neither is significant. Interestingly and similar to white Americans, there is also some weak evidence that obesity rates for women declined as a consequence of the recession.

4.6 Conclusions

In this paper, we showed that the Great Recession resulted in worse health outcomes. We built on previous work by employing more granular information on local macroeconomic conditions by using the geocode file from the Panel Study of Income Dynamics. Specifically, we showed that a one percentage point increase in the unemployment rate results in a 7.8-8.8 percent increase in reports of poor health. In addition, increases in unemployment are also associated with worse mental health and increases in reports of chronic drinking. The bulk of our effects were borne by whites, the less educated, and women. We do not uncover any evidence that macroeconomic measures at larger levels of aggregation have larger effects than at smaller levels and, thus, this paper provides no evidence of spillovers.

Our findings are not consistent with most of the aggregate studies in this literature in that we do not find compelling evidence that any of our health measures improved during the Great Recession. However, they are consistent with a growing body of evidence that employs individual-level data and shows that health tends to deteriorate when the economy worsens. Moreover, we show that the people who were the most impacted were less educated, white, female, and younger than age 55. This is consistent with important recent findings by Case and Deaton (2015) who show that mortality of less educated whites has risen over the period 1999-2013.

Chapter 5

The Effect of Education on Adult Health: Evidence from China

5.1 Introduction

The correlation between education and health is well established in different countries by difference races and by different life cycles.[5] Generally, people who acquire more education have better health outcomes. Some policy makers have started to consider improving health outcomes through education. For example, the UK planned to increase the legal age that a student may leave school and one of the important objectives of that policy is to improve health outcomes. In order to assess the benefits of improving education, accurate estimates are needed to provide any recommendations before governments can implement any policies. However, the literature on the causal effect of education on health, as one of the most important non-monetary returns of education, has not had any consistent results so far. For example, Lleras-Muney (2005) measures the causal effect of education on health in the US and she finds that an additional year of schooling lowers the probability of dying in the next 10 years by at least 3.6 percent. While Clark and Royer (2013) find there is little evidence to show that more education improves health outcomes and changes in health behaviors in the UK. Meghir et al. (2012) use register data from Sweden and find mixed results for the effects of education on mortality and small educational effects on morbidity.. Meghir et al.'s (2012) finding are inconsistent for different countries and even when focused in the same country, the effects of education on health remain a debated topic.[6]

In addition, the importance of the causal relationship between education and health has been

[5] See review papers Grossman (2006), Culter and Lleras-Muney (2006), Oreopoulos and Salvanes (2011).
[6] Fletcher (2015) does not find causal effects of education on health in US. Similarly, in the UK, Silles (2009) finds that higher education improves human health, while Clark and Royer (2013) do not find beneficial effects of education on health.

already raised by a series of studies, however, the available evidence is mainly from US, UK, and other developed countries. It is not clear whether the estimates from high-education countries could be used as a reliable guide for developing countries, where the average educational attainment is much lower compared to more developed countries. This paper provides new evidence of the effects of education on health in China by using a novel quasi-experimental framework to fill the literature gap. In particular, this study attempts to address the issue of endogeneity by using the 1977 Resuming College Entrance Exam Policy in China as an instrumental variable to account for the potential strong endogeneity between education and health. In 1977, China reformed higher education after the end of the Cultural Revolution (1966-1976) that disrupted the regular educational system for about 11 years. In particular, the universities stopped recruiting new students from 1966 to 1971, and only began a small amount of recruitment that was not based on academic performance in 1972. On Oct. 21, 1977, the Ministry of Education in China released a public announcement that standard university recruitment policies will be re-instituted and the first national university entrance exam was taken on December 11 in 1977.

The 1977 Resuming College Entrance Exam Policy provides valuable and reliable evidence to evaluate the relationship of education and long-term health outcomes at older ages. The Cultural Revolution stopped standard university level education in China for up to 11 years.. This disruption affected educational attainment for about 11 years of young cohorts at that time. When compared to the smaller cohorts and smaller portion of population affected by the compulsory laws in the UK and US (Oreopoulos 2006, Lleras-Muney 2005), such a large scale effect is very rare and should provide evidence through other channels which are omitted by earlier studies.

This paper makes three primary contributions to the existing literature on the effects of education on health. First, since there are still no consistent results on the relationship between education and health, this study extends the existing literature by providing further evidence on the debate of the effectiveness of education on health. Second, this paper develops a novel research design to estimate the educational returns on health in China. This design uses plausibly exogenous variation in schooling in China, which has never been studied in evaluating educational effects on health. The solution to the problem of endogeneity of education is to use the 1977 Resuming College Entrance Exam Policy in China as an instrument. Most existing studies use compulsory laws in developed countries (US, UK, Germany, Sweden, etc.), however evidence from developing countries is relatively rare.[7] It is known that educational attainment is much higher in developed countries than in developing countries. This study provides evidence for the relationship between education and health in China and should present a different picture of this important topic from a developing country. Third, this paper tries to provide evidence on the possible mechanisms through which education may affect health outcomes, including health behaviors and cognition. Although there are many studies that discuss the possible mechanisms, most do not provide solid evidence to answer this important question.[8]

The results generally suggest that education has a positive effect on health in China. Specifically, one additional year of schooling increases height by 1.5 cm and grip strength by 0.14 standard deviations. I do not find any statistically significant effects on mental health. I further divide the samples by gender. The estimates from 2SLS suggest that one additional year of schooling reduces the number of IADL by 0.16, increases grip strength by 0.26 standard deviations, and height by 2.8 cm for men. I do not find any statistically significant effects for women.

Additionally, this study explores the possible mechanisms through which education may affect health: cognition and health behaviors. The results show that increases in education does not increase health outcomes through cognition and health behaviors in China.

Lastly, I estimate the effects of education on health by birth area (rural versus urban). As expected, the main result is driven by those born in rural areas where disruption to education affected living conditions much more severely than in urban areas.

[7] Huang (2015) uses the compulsory law in China to estimate the causal relationship between education and health and he focuses on working age samples. Fang et al. (2012) also uses the compulsory law in China as well to measure the causality between education and health.

[8] Culter and Lleras-Muney (2006) raised three possible ways through which education may affect health: differences in economic resources, different time preferences and different level of knowledge.

The findings have several policy implications. First, as the Chinese population ages, they will need a lot of social resources to support the increasing elderly population. The evidence on the effects of education on health and cognitive abilities will help to shed some light for policy makers who are planning to solve the severe aging problem. Second, China is planning to increase the current compulsory education from 9 to 12 years. This policy has the potential to significantly increase the average level of education in China, especially in rural areas, where high school dropout rates are high. The results from this study can provide additional evidence on the returns to education and give policymakers more faith for putting more effort to increase educational levels in China.

The rest of the paper is laid out as follows. In section II, I introduce some background information on the Chinese higher education reform that occurred in 1977. In section III, I provide details of my data, then identification methods in section IV. In section V, I explain the results. Finally, in section VI, I conclude with the main results.

5.2 1977 Resuming College Entrance Exam Policy in China

The Chinese Ministry of Education released the public announcement that they will re-institute higher education on Oct. 21, 1977. It marked the end of 11 years of interruption to the formal education system in recent Chinese history. From 1966 to 1976, China experienced a political campaign that threw millions of Chinese people into chaos and a revolutionary struggle (Giles, Park and Wang (2008)). Economic development and social progress was greatly hindered during these turbulent ten years.

University level education was interrupted for 11 years. From 1966 to 1971, there was no normal university teaching and new student recruitment. Although the universities started to admit a small number of new students from 1972, the admission process only relied on political attitude or family background that “poor farmers”, “workers”, and those who have “revolutionary” backgrounds were preferred. Academic performance and records were not primary indicators for admission by universities until Oct. 21, 1977. The Chinese government then decided to restore the college entrance exams and students would enroll the students based on competitive entrance examinations. This policy put the educational back on track. The important implication of the 1977 Resuming College Entrance Exam Policy lies in the signal that knowledge is important and useful. and that society had begun to respect people with higher levels of education. The announcement by the Ministry of Education was an important development that not only affected applicants who just graduated from high school, but also gave hope to younger cohorts who wanted to pursue higher education and to help them stay in school longer.

5.3 Data

I use the 2011 and 2013 waves of the China Health and Retirement Longitude Survey (CHARLS) to estimate the returns to education on health outcomes, cognition, and health behaviors. CHARLS interviewed about 10,000 households and 17,500 individuals in 150 counties/districts and 450 villages/resident committees across 28 provinces every two years. The individuals sampled in CHARLS are all aged 45 and older. The topics included in CHARLS are demographics, family structure, health status and functioning, biomarkers, income and consumption..

Based on the eligibility of applicants of university entrance examinations released by Ministry of Education in 1977, the youngest applicants should be 18 years old. Our treatment group is individuals who just turned 18 years old in 1977 and the control group is individuals who were 19 years old and older in October 1977 and interrupted by the closed out of universities before 1977. The samples are restricted to individuals who were born after 1955. Since CHARLS respondents are all 45 years old and older, the youngest samples are those who were born in 1968.

Table 5.1: Summary Statistics

	Obs.	Mean	Std. Dev.
Years of Schooling	12275	6.98	4.27
Excellent Health	12792	0.27	0.44
Pessimistic on expected age	10181	0.27	0.44
Number of IADL	13081	0.24	0.75
Lung Capacity	9437	296.50	116.10
Grip Strength	9577	33.02	10.66
Height	9744	159.38	8.21
Average number of words recall	11232	4.02	1.66
Number measurement	11804	3.05	1.92
Awareness of Date	13104	3.58	1.70
CES_D	11468	6.73	5.41
Ever Smoke	13033	0.39	0.49
Drink last year	13009	2.36	0.88
Age	13104	51.34	3.76
Men	13097	0.46	0.50
Father Literacy	6876	0.22	0.41
Father Primary School	6876	0.15	0.36
Father Middle School	6876	0.10	0.30
Mother Literacy	6863	0.08	0.27
Mother Primary School	6863	0.10	0.30

Source: CHARLS 2011 wave and 2013 wave.

I present summary statistics in Table 5.1. The average years of schooling for all of the samples is 7 years. The demographic control variables in this study include age, age square, gender, parents' education, and whether the individual was born in the Great Chinese Famine years. The average age for all of the samples is about 51 years old.

The health outcomes mainly include two parts: physical health outcomes and mental health outcomes. For the physical health outcomes, I include excellent health status[9], whether the individual feels pessimistic for surviving until 75 years old[10], number of IADL[11], and biomarkers which including lung capacity, grip strength, and height.

Cognitive abilities measured in this study are: average number of words recalled[12], number measurements[13], and awareness of the date[14]. Mental health is measured by the Center for Epidemiological Studies Depression (CES_D) scale. It includes questions asking about whether the individual felt bothered in the past 30 days, felt troubled, and felt unhappy, etc[15]. Each question was scaled on one of four levels: rarely, some or a little, occasionally, or most or all of the time. Each level was given a score from 0 to 3. Finally, I measure health behaviors, which include whether the individual has ever smoked and whether drank last year.

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[9] Excellent health is dummy which equals to 1 if they report to have excellent or very good health status.

[10] Pessimistic until survival to age 75 (if the respondent is less than 65) is define as individuals who report that almost impossible or not very likely to live until 75 years old.

[11] The number of IADL includes having difficulties with doing household chores, preparing hot meals, shopping for groceries, managing your money, such as paying bills or managing assets, etc, and taking medications.

[12] CHARLS interviewers read a list of 10 words and ask the respondents to recall these words immediately and a little while later. We constructed the variable of average number of words recall by taking the average numbers of words they can recall for the two times.

[13] In addition, they also need to calculate the subtraction of 7 from 100 for up to 5 times. This is 100 minus 7 (which is equal to 93), and subsequently minus 7 one more time (100 - 7 - 7 = 86) and so on. If they can get 93 for the first time, they obtain one more credit. Subsequently get 86, they gain another one more credit.

[14] Awareness of date is measured by the number of whether the respondents can tell the correct date, month, year, day of the week and day of the season.

[15] CES_D includes the following 10 questions: whether feel bothered in the past 30 days, whether feel troubled keeping mind, and whether feel depressed, whether feel everything was effort, fearful, restless, lonely, whether feel could not get going, hopeless, and unhappy.

5.4 Identification Strategy

When estimating the returns to health, educational attainment is acknowledged as an endogenous variable. To identify the causal relationship between education and its returns, it is common to use an instrument to control for the endogeneity. The instrumental variable should be correlated with educational attainment, but should not be correlated with the health outcome variables except through the effect of educational attainment. The changes in educational attainment generated by the 1977 Resuming College Entrance Exam Policy provide us an opportunity to estimate the returns to education in China in terms of health outcomes, cognition and health behaviors.

5.4.1 Years of Schooling and the 1977 Resuming College Entrance Exam Policy (First Stage of 2SLS)

The effect on educational attainment stemming from the 1977 Resuming College Entrance Exam Policy can be summarized as the following linear regression model:

$$S_{it} = \beta_0 + \beta_1 1977\ Policy + \beta_2 X_{it} + \gamma_{birthcounty} + \delta_t + \omega_{bt} + \vartheta_{it} \qquad (1)$$

where S_{it} is the individual's years of schooling in year t. 1977 Policy is a dummy variable that equals 1 if the individual was less than 18 years old in 1977 September. X_{it} is a set of control variables that includes age, age square, sex, parents' education, and whether the individual was born in the Great Famine years (1959-1961). ϑ_{it} is the unobserved determinants of years of schooling. I further control for county fixed effects, year fixed effects, and province-specific birth year linear trends in this estimation.

5.4.2 Health Returns of Education

The relationship between education and adult health outcomes can be expressed as:

$$H_{it} = \alpha_0 + \alpha_1 S_{it} + \alpha_2 X_{it} + \mu_{birthcounty} + \theta_t + \varphi_{bt} + \varepsilon_{it} \qquad (2)$$

where H_{it} denotes adult outcomes including health outcomes and health behaviors discussed in session III. S_{it} denotes years of schooling, and X_{it} is the same set of control variables mentioned in the previous specification. I also control for birth county fixed effects, year fixed effects, along with province specific birth year trends. ε_{it} is the error term that includes omitted variables and might be correlated with education. Hence, OLS estimation may be biased and I use the 1977 Resuming College Entrance Exam Policy as instrument to conduct IV estimation. Equation (2) combined with equation (1) can estimate α_1 via 2SLS.

5.5 Result

I begin by examining the effect of the 1977 Resuming College Entrance Exam Policy on education. Then in the following results sections, I report the effects of education on health, health behaviors and cognition.

5.5.1 The Impact of the 1977 Resuming College Entrance Exam Policy on Education

I present the effects of the 1977 Resuming College Entrance Exam policy on education attainment in Table 5.2. All regressions include a vector of demographic control variables, which are outlined in equation (1). Each row represents a different regression, where the dependent variables in each row are health outcomes, health behaviors and cognition. Column 1 is regression estimates for all samples, while columns 2 and 3 are estimates for men and women, respectively. Robust standard errors clustered at the birth county and birth month level are shown in parentheses.

The results in Column 1 suggest that the cohorts born after 1959 September have about one more year of schooling (14.3 percent to the mean) on average than cohorts born before 1959 September. It is important to note that the effect is smaller in magnitude for women than for men. Results in column 2 and column 3 imply that men who were born after 1959 September have 0.90 more years of schooling, while women who were born after 1959 September have 1.21 more years of schooling. As expected, parents' educational background has a significant impact on their children's educational outcomes. For example, individuals whose father attended middle school are likely to increase their years of schooling by 1.33 years than individuals whose father

Table 5.2: The Impact of the Higher Education Reform in 1977 on Education

	Year of Schooling		
	Column 1	Column 2	Column 3
	All Sample	Men	Women
Policy	1.001***	0.897**	1.212***
	[0.247]	[0.377]	[0.371]
Age	2.356***	2.653***	2.647***
	[0.586]	[0.760]	[0.652]
Age squared	-0.021***	-0.018***	-0.024***
	[0.004]	[0.005]	[0.006]
Father Literacy	2.371***	0.696***	1.083***
	[0.123]	[0.197]	[0.190]
Father Primary School	0.891***	1.171***	1.270***
	[0.142]	[0.253]	[0.233]
Father Middle School	1.334***	1.358***	1.769***
	[0.156]	[0.305]	[0.286]
Mother Literacy	1.651***	-0.124	0.926***
	[0.217]	[0.263]	[0.216]
Mother Primary School	0.535***	1.110***	1.389***
	[0.178]	[0.319]	[0.328]
Born in Great Chinese Famine (1959-1961)	1.315***	0.071	-0.115
	[0.237]	[0.239]	[0.239]
Observations	6,101	2,595	3,506

Note: *significant at the 10% level; **significant at the 5% level; ***significant at the 1% level. In all the regressions, I have controlled for the demographic background variables shown in Table 5.1. The regressions controlled for birth county dummies, year fixed effects and province specific birth year linear trend and clustered at birth year and month and birth county level.

is illiterate. Results thus far have shown that the 1977 policy did increase educational levels.

5.5.2 The Effects of Education on Health Outcomes and Heterogeneity

I provide a summary of OLS and IV regression results in Table 5.3 Panel A for physical health outcomes and mental health outcomes. Each entry corresponds to a different regression, where the dependent variables are measured as physical health outcomes and mental health outcomes and the independent variable is years of schooling. As shown in the above section, regression estimates are weighted by those provided in the CHARLS survey and the standard errors are clustered on both birth county and birth month. OLS estimates suggest that the relationship between education and health is positive, i.e. higher educational attainment increases an individual's physical health. For example, one additional year of schooling increases the probability of being in excellent health by 0.7 percentage points meanwhile reducing the number of IADL by 0.02. There is also evidence to indicate that an additional year of schooling increases lung capacity by 0.022 standard deviations, increases grip strength by 0.023 standard deviations, and height by 0.165cm.[16] Since lung capacity, grip strength, and height are measured in the field by trained interviewers, these three measurements should be more precise than the self-reported health outcomes. However, when I use the 1977 Resuming College Entrance Exam Policy as an instrument, most of the coefficients on years of schooling are no longer significant. I only find statistically significant educational effects on grip strength and height. In particular, one additional year of schooling increases grip strength by 0.14 standard deviations and increases height by 1.486 cm. As for mental health, I do not find any statistically significant effects on CES-D. In conclusion, OLS estimates show that education has significant effects on physical health outcomes, but IV estimates only find significant effects on grip strength and height in China.

In Table 5.4 Panel A, I split the results by gender. The OLS estimates suggest that more schooling improves both men's and women's physical health in general. For example, an

[16] z score of lung capacity and z score of grip strength are generated by the absolute value of lung capacity/grip strength minus the mean and divided by the standard deviation of lung capacity/grip strength.

additional year of schooling increases the probability of being in excellent health by 1.1 percentage points for men and 0.4 percentage points for women. An additional year of schooling also increases lung capacity, grip strength, and height for both men and women. When turning to 2SLS estimates, an additional year of schooling decreases men's number of IADL by 0.16 which accounts to 66.7 percent to the mean. One more year of schooling is also associated with increases in lung capacity by around 0.27 standard deviations and height by 2.8 cm. There is evidence to show that the educational impact on health is larger for men than for women. Again, there is no statistically significant effect on mental health when we look at men and women separately.

Table 5.3: The Effects of Education on Health for All Samples

	OLS		2SLS		F Stat.	N
Panel A: Physical Health and Mental Health						
Excellent Health	0.007***	[0.002]	0.026	[0.033]	13.64	6,040
Pessimistic on expected age	-0.016***	[0.002]	-0.019	[0.028]	14.08	5,054
Number of IADL	-0.022***	[0.004]	-0.079	[0.052]	13.77	6,089
Lung Capacity (z score)	0.022***	[0.004]	0.013	[0.067]	11.42	4,710
Grip Strength (z score)	0.023***	[0.004]	0.141*	[0.078]	10.43	4,771
Height	0.165***	[0.031]	1.486**	[0.657]	9.77	4,855
CES_D	-0.183***	[0.027]	0.075	[0.420]	11.47	5,707
Panel B: Cognition and Health Behaviors						
Average number of words recall (z score)	0.084***	[0.004]	0.06	[0.073]	11.75	5,613
Number measurement	0.149***	[0.008]	0.213	[0.136]	13.32	5,881
Awareness of Date (z score)	0.065***	[0.004]	0.055	[0.052]	13.46	6,101
Ever Smoke	-0.003*	[0.001]	0.017	[0.024]	13.54	6,070
Drink last year	-0.011***	[0.004]	-0.017	[0.057]	13.75	6,058

Note: *significant at the 10% level; **significant at the 5% level; ***significant at the 1% level. In all the regressions, I have controlled for the demographic background variables shown in Table 5.1. The regressions controlled for birth county dummies, year fixed effects and province specific birth year linear trend and clustered at birth year and month and birth county level.

Table 5.4: The Effects of Education on Health by Gender

	Men				Women			
	OLS		2SLS		OLS		2SLS	
Panel A: Physical Health and Mental Health								
Excellent Health	0.011***	[0.003]	0.056	[0.058]	0.004*	[0.003]	0.002	[0.036]
Pessimistic on expected age	-0.020***	[0.003]	-0.014	[0.054]	-0.015***	[0.003]	-0.037	[0.030]
Number of IADL	-0.033***	[0.007]	-0.156*	[0.092]	-0.015***	[0.004]	-0.069	[0.053]
Lung Capacity (z score)	0.043***	[0.007]	0.169	[0.114]	0.013**	[0.006]	-0.044	[0.081]
Grip Strength (z score)	0.045***	[0.008]	0.256*	[0.147]	0.018**	[0.007]	0.161	[0.116]
Height	0.260***	[0.054]	2.842**	[1.332]	0.133***	[0.040]	0.47	[0.529]
CES_D	-0.209***	[0.040]	-0.826	[0.841]	-0.166***	[0.037]	0.527	[0.439]
Panel B: Cognition and Health Behaviors								
Average number of words recall (z score)	0.082***	[0.007]	-0.08	[0.179]	0.082***	[0.006]	0.150**	[0.073]
Number Measurement	0.136***	[0.012]	0.470*	[0.266]	0.145***	[0.011]	0.186	[0.136]
Awareness of Date (z score)	0.063***	[0.006]	0.044	[0.084]	0.066***	[0.005]	0.054	[0.059]
Ever Smoke	-0.006*	[0.003]	0.044	[0.054]	-0.002**	[0.001]	0.008	[0.014]
Drink last year	-0.019***	[0.007]	-0.127	[0.124]	-0.005	[0.003]	0.01	[0.049]

Note: *significant at the 10% level; **significant at the 5% level; ***significant at the 1% level. In all the regressions, I have controlled for the demographic background variables shown in Table 5.1. The regressions controlled for birth county dummies, year fixed effects and province specific birth year linear trend and clustered at birth year and month and birth county level.

The effects of education on health by birthplace are shown in Table 5.5 Panel A. The OLS estimates for both samples born in rural and urban areas generally suggest that education has positive effects on physical health outcomes. However, rural born samples are seen to have benefited more from the increase in education. The estimates from rural born samples are significant for all the outcome variables that are measured in this study, while only some of the health outcomes are statistically significant. Similar trends are found in the 2SLS estimation. The 2SLS estimates imply that one additional year of schooling decreases the probability of being pessimistic on expected age by 7 percentage points (26 percent to the mean). One more year of education is also associated with increases in grip strength by 0.2 standard deviations for the individuals who were born in the rural area. An additional year of schooling also increases height for rural born samples by about 1.1 cm. However, I do not find any statistically significant educational effects on health for urban born samples. Given the fact that rural samples suffered much more in terms of disruptions to education and have relatively poorer living conditions in 1960s and 1970s compared to those born in urban areas, it is not surprising to find that the educational effects on health in rural samples are much larger than the urban-born samples.

5.5.3 Health Behaviors and Cognitive Abilities

It is important to know whether education changes health behaviors, since health behaviors can be very good predictors for health outcomes later in life. As shown in Panel B of Table 5.3, OLS estimates indicate that additional year of schooling decreases the probability of reporting whether an individual has ever smoked and drank in the last year, while the 2SLS estimates are no longer significant. I further explore the educational effects on health behaviors by gender in Table 5.4 Panel B. Both men and women do not show any statistically significant effects from the IV estimation.

Table 5.5: The Effects of Education on Health by Rural/Urban

	Rural				Urban			
	OLS		2SLS		OLS		2SLS	
Panel A: Physical Health and Mental Health								
Excellent Health	0.007***	[0.002]	0.036	[0.032]	0.006	[0.008]	-0.049	[0.134]
Pessimistic on expected age	-0.013***	[0.002]	-0.070*	[0.041]	-0.012**	[0.006]	0.085	[0.062]
Number of IADL	-0.022***	[0.004]	-0.076	[0.055]	-0.022*	[0.012]	-0.041	[0.160]
Lung Capacity(z score)	0.021***	[0.004]	0.084	[0.063]	0.024	[0.018]	-0.284	[0.233]
Grip Strength(z score)	0.022***	[0.004]	0.206**	[0.096]	0.026	[0.017]	-0.081	[0.130]
Height	0.190***	[0.033]	1.067**	[0.544]	-0.089	[0.124]	2.663	[1.803]
CES_D	-0.175***	[0.030]	0.102	[0.479]	-0.158**	[0.077]	0.569	[0.806]
Panel B: Cognition and Health Behaviors								
Average number of words recall (z score)	0.081***	[0.005]	0.096	[0.078]	0.082***	[0.017]	0.100	[0.172]
Number measurement	0.157***	[0.008]	0.183	[0.141]	0.103***	[0.031]	0.039	[0.324]
Awareness of Date (z score)	0.069***	[0.004]	0.109*	[0.058]	0.024	[0.015]	-0.132	[0.195]
Ever Smoke	-0.002	[0.002]	0.011	[0.024]	-0.001	[0.005]	0.054	[0.091]
Drink last year	-0.012***	[0.004]	-0.048	[0.054]	-0.024*	[0.014]	0.088	[0.247]

Note: *significant at the 10% level; **significant at the 5% level; ***significant at the 1% level. In all the regressions, I have controlled for the demographic background variables shown in Table 5.1 The regressions controlled for birth county dummies, year fixed effects and province specific birth year linear trend and clustered at birth year and month and birth county level.

As we can expect, people with higher education should take less-risky health behaviors, i.e. less smoking and drinking, et cetera. However, as the average level of education in China is still much lower than the average education level in the developed countries, especially when we focus on the sample born in earlier times. As shown in Table 5.1, the average years of schooling for the samples is about 7 years old, it may still be too low for these less educated people to learn about the potential risk that they may face when undertaking unhealthy lifestyles.

Table 5.3 Panel B also illustrates the estimates for cognitive abilities. First, we can see that education significantly increases the cognitive abilities of the elderly in all kinds of measurements for OLS estimation: average number of words recall, number measurements, and awareness of the date. As for the 2SLS estimates, there are no statistically significant effects at all.

By splitting the estimation by gender in Table 5.4 Panel B, I find some educational effects on cognition for both men and women. Specifically, the 2SLS estimations for men suggest that one additional year of schooling increases the number of measurements by 0.47, while for women I find that one additional year of schooling increases average words recall by about 0.15.

The results in Table 5.5 Panel B present the educational effects on health by birthplace. OLS estimation results shows that both samples born in rural and in urban areas have higher cognitive abilities when obtaining additional years of schooling,. However, I only find statistically significant educational effects for rural born samples in the 2SLS estimation. Specifically, one additional year of schooling increases date awareness by 0.11 standard deviations.

5.6 Robust Tests

One possible concern that might invalidate the IV estimation is that the birth province (Hukou) might not be the location where the individuals in the samples attended school. Thus, an individual's mobility is considerably important. I present information of the sample mobility in

Table B.1. It shows that the sample was relatively immobile. About 52% of the samples' current locations are exactly the same as where they were born and 37% of the sample moved to another village in the same county. When we take a look at the sample that migrated, only 9% of the sample moved to another county in the same province and 2% of the samples moved to another province. When comparing the mobility between females and males, females tend to be more mobile than males. About 78% of males stayed in the village where they were born, while only 29% of females stayed in the same village. It is reasonable that women tend to migrate to their husband's location after they get married. However, even for the women that migrated, only 11% moved to another county in the same province and another 3% moved to another province. In conclusion, the migration between counties and provinces was very limited in China because of the strict household registration system. In order to control for unobservable confounding factors, all regressions in this paper include birth county dummies.

The Chinese Great Famine (1959-1961) is another issue that may contaminate the results. It is one of the worst famines in human history that involved all regions in China. Li and Yang (2005) recorded that the great famine caused about 16.5 and 30 million deaths. Almond et al. (2010) concluded that fetal exposure to the great famine had negative effects on socioeconomic outcomes. In this paper, I present another set of estimations, which drop the cohorts born between 1959 and 1961. I present the estimates where I drop all samples who were born in the famine years (1959-1961) in Table 5.6. The cognitions are still statistically significant, that is, one more year of schooling increases the number of measurement by 0.28 and the awareness of date by 0.09 standard deviations, while none of the health outcomes are significant any more. This may due to the fact that I drop all the samples that were most likely to be affected by the policy directly.

Another concern is whether province specific linear trends may affect the estimation, which could be lead by factors like economic growth. To deal with this concern, all the above estimations include province-specific birth year trends and the estimates are consistent with the estimation without controlling for these trends. This suggests that province-specific birth year trends do not drive the estimation.

In addition, I present a placebo test in Table 5.7. I include the samples that were born between 1949 and 1962 and use the placebo IV of being older than 18 in 1953. None of the health outcomes along with health behaviors and cognition are statistically significant as shown in Table 5.7. At last, I present the results when I regress on the outcomes on the 1977 policy

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Table 5.6: The Effects of Education on Health without Samples Born in Famine Years

	OLS		2SLS		F Stat.	N
Panel A: Physical Health and Mental Health						
Excellent Health	0.007***	[0.002]	0.045	[0.028]	18.99	4,948
Pessimistic on expected age	-0.015***	[0.002]	0.000	[0.026]	17.92	4,127
Number of IADL	-0.021***	[0.004]	-0.075	[0.049]	19.64	4,984
Lung Capacity (z score)	0.022***	[0.005]	-0.068	[0.069]	15.30	3,866
Grip Strength (z score)	0.024***	[0.005]	0.012	[0.053]	15.51	3,905
Height	0.146***	[0.036]	0.495	[0.448]	15.29	3,985
CES_D	-0.193***	[0.030]	0.048	[0.337]	18.30	4,661
Panel B: Cognation and Health Behaviors						
Average number of words recall (z score)	0.088***	[0.005]	0.094	[0.061]	19.00	4,600
Number measurement	0.152***	[0.009]	0.278**	[0.111]	20.73	4,814
Awareness of Date (z score)	0.068***	[0.004]	0.091*	[0.048]	19.03	4,996
Ever Smoke	-0.003**	[0.002]	0.015	[0.022]	19.08	4,971
Drink last year	-0.010**	[0.004]	-0.014	[0.052]	19.54	4,959

Note: *significant at the 10% level; **significant at the 5% level; ***significant at the 1% level. In all the regressions, I have controlled for the demographic background variables shown in Table 5.1. The regressions controlled for birth county dummies, year fixed effects and province specific birth year linear trend and clustered at birth year and month and birth county level.

Table 5.7: The Effects of Education on Health for All Samples (Placebo Test)

	OLS		2SLS		N
Panel A: Physical Health and Mental Health					
Excellent Health	0.005***	[0.002]	-0.055	[0.098]	6,971
Pessimistic on expected age	-0.015***	[0.002]	0.030	[0.155]	5,767
Number of IADL	-0.024***	[0.004]	-0.206	[0.213]	7,023
Lung Capacity (z score)	0.027***	[0.004]	0.43	[0.344]	5,550
Grip Strength (z score)	0.022***	[0.004]	0.139	[0.147]	5,615
Height	0.156***	[0.031]	1.93	[1.613]	5,711
CES_D	-0.169***	[0.024]	0.649	[1.174]	6,513
Panel B: Cognation and Health Behaviors					
Average number of words recall (z score)	0.079***	[0.004]	0.434	[0.317]	6,424
Number measurement	0.156***	[0.007]	-0.452	[0.577]	6,759
Awareness of Date (z score)	0.071***	[0.003]	-0.091	[0.194]	7,040
Ever Smoke	-0.002	[0.001]	0.015	[0.022]	7,006
Drink last year	-0.008**	[0.003]	-0.225	[0.235]	6,994

Note: *significant at the 10% level; **significant at the 5% level; ***significant at the 1% level. In all the regressions, I have controlled for the demographic background variables shown in Table 5.7. The regressions controlled for birth county dummies, year fixed effects and province specific birth year linear trend and clustered at birth year and month and birth county level.

Table 5.8: Regression on Policy IV

	OLS		N
Excellent Health	0.031	[0.033]	6,447
Pessimistic on expected age	-0.033	[0.033]	5,372
Number of IADL	-0.083	[0.053]	6,498
Lung Capacity (z score)	0.030	[0.070]	5,021
Grip Strength (z score)	0.139**	[0.063]	5,093
Height	1.371***	[0.474]	5,182
CES_D	0.087	[0.391]	6,084
Average number of words recall (z score)	0.076	[0.075]	6,003
Number measurement	0.211	[0.142]	6,278
Awareness of Date (z score)	0.068	[0.054]	6,510
Ever Smoke	1.028	[1.915]	6,478
Drink last year	-0.028	[0.058]	6,466

Note: *significant at the 10% level; **significant at the 5% level; ***significant at the 1% level. In all the regressions, I have controlled for the demographic background variables shown in Table 5.8. The regressions controlled for birth county dummies, year fixed effects and province specific birth year linear trend and clustered at birth year and month and birth county level.

directly in Table 5.8. The results are very consistent with the 2SLS results shown in Table 5.2. In particular, only grip strength and height are statistically significant.

5.7 Conclusion

This study uses CHARLS to estimate the causal effects of education on adult health outcomes, health behaviors, and cognitive abilities using the 1977 Resuming College Entrance Exam Policy in China as instrument. In particular, the 1977 Resuming College Entrance Exam Policy has significant and large effects on years of schooling (1.2 years for female, 0.9 years for male).

The results suggest that education has positive effects on health outcomes. In particular, I find that one additional year of schooling increases height by 1.5 cm and grip strength by 0.14 standard deviations. I also explore two ways that education may affect health: cognitive abilities and health behaviors. However, the results imply that education does not improve health through cognitive abilities and health behaviors. When I split the results by gender, I find one additional year of schooling decreases the number of IADL by 0.16, increases grip strength by 0.26 standard deviations, and height by 2.8 cm for men, however there is no statistically significant effects for women. Further, I estimate the effects of education on health by the groups who were born from different areas (rural and urban). As expected, the positive effects of education on health is mainly driven by rural born samples, since rural areas were exposed to much severe working conditions and educational interruption.

This study supports the view that education improves health outcomes (Lleras-Muney (2005), Silles 2009). When I split the samples by gender, I find men tend to have much larger effects than for women. This may be due to the fact that China has a strong historical preference to having sons and most families invest their resources to sons rather than daughters.

Chapter 6

Do older siblings obtain more? Birth order matters in China

6.1 Introduction

Economists have long been interested in exploring the factors that shape an individual's capital accumulation. There is an extensive literature that examines the birth order effect on educational attainment for the last several decades (Zajonc (1976), Hauser and Sewell (1985), Kessler (1991), Black, Deverux, and Salvanes (2005)). The research studies in earlier decades found mixed effects, while the more recent studies seem to come to the consensus that first borns are more likely to acquire higher education, IQ scores, and earnings (Black, Deverux and Salvanes (2005, 2011), Booth & Kee (2009), Bu (2014)). Besides education, health is also considered an important input to human capital accumulation. There is substantial literature estimating the birth order effect on adult health outcomes, however, most of these studies are mainly in the medical fields. Research studies in the economic fields are restricted to very limited health outcome variables and small sample sizes.[17] Another limitation of the existing literature on birth order is that most of the studies focus on estimating the birth order effect in developed countries. This study fills the literature gap by estimating the birth order effect on health in the largest developing country, China, and measures health outcomes that are rarely studied.

One challenge in estimating the birth order effect on education or health lies in the fact that birth order is related to family size and other familial background information. For example, first born children are more likely to be from a small family compared with later born and later-born children are more likely to come from large families. Furthermore, first born children are also more likely to be born to younger parents (Black, Deverux & Salvanes (2016)). To address this

[17] The health outcomes in the earlier literature are limited to mortality rate, height, weight and some diseases which will be introduced in the literature later.

concern, a large-scale survey is needed which should include detailed information that can sufficiently account for across-family differences, such as family size, parents' education, parents' age at birth, et cetera.

In this paper, I study the birth order effect on health outcomes in China and also explore the possible mechanisms in which birth order may affect health. I use two methods to identify the birth order effect. First, I run a regression of the birth order effect on health outcomes by different family types and control for the parents' age and education, among other factors. By using this model, I do not need to worry about omitted family background factors, such as the reason why a family might have three children rather than five children. Although I can solve the omitted family background information problem by using the above method, another issue that I have is that the sample size is small. Hence, I use the relative birth order and a birth order index, which was used by Ejmaes and Portner (2004) and Booth and Kee (2009) to solve the small sample problem. The detailed procedure to construct the two measures is illustrated in the methods section.

This paper makes three primary contributions to the existing literature. First, studies that estimate the relationship between birth order and health outcomes in China is limited. Furthermore, the existing literature of the birth order effect on health outcomes is mainly studied in the medical literature. Black et al. (2016) is an exception, which used Norway register data to examine birth order effects on many physical health outcomes, mental health outcomes, and health behaviors. The Chinese context is important and special in estimating birth order effects in the following aspects. First, China is the most populous country in the world with a population of more than 1.3 billion people. The exiting literature mainly focuses on developed countries. This study uses a sample of individuals who were born in the 1950s and 1960s when the fertility rate was extremely high in China.[18] Sibling sizes in existing studies that focused on developed countries usually had two to four children. My study on China should provide the birth order effect on health outcomes from a different perspective.

[18] The average number of children that a female gave birth to in the 1950s and 1960s was about 6.

China also has a long history of son-preference and an especially strong preference for a first boson. Historically, the eldest-son would inherit property by right of their primogeniture. This custom is deeply rooted in Chinese culture and has continued to affect parental investment decisions in modern society. Hence, studying China can provide us with a different perspective on the birth order effect which cannot be obtained from previous studies that focused on developed countries.

Finally, the current literature on birth order which studied health outcomes based on relatively young samples cannot account for different types of diseases that can only be observed in relatively older samples. In this study, the sample includes individuals aged 45 years and over, which is old enough to capture health problems.

By controlling for sufficiently related control variables which might contaminate the birth order effect, I use the longitudinal CHARLS data to estimate the birth order effect on health outcomes. The results suggest that first born children have better health outcomes compared with later born children, although the effects are not very strong. For example, in two children and three children families, later born children have a worse overall health status when compared to the first born children. There is some evidence to show that later born children have more number of IADL[19] in four children families. When I further investigate the birth order effects by gender, the results show that first born sons have better health outcomes relative to later born sons. For instance, first born sons have a smaller likelihood of having poor health compared with later born children in two and three children families. In addition, first born sons have less number of IADL, lower depression scales when we compare them with later born sons. However, there are no statistically significant effects for women. When I use the relative birth order or new birth order index as done by Ejmaes and Portner (2004) and Booth and Kee (2014), the results are generally consistent with the trends we discussed above: there is some evidence to show first born children have better health outcomes and the birth order effect is especially strong for first born sons.

[19] The number of IADL is defined by reporting following difficulties with: (1) doing household chores; (2) preparing hot meals; (3) shopping for groceries; (4) managing your money, such as paying your bills, keeping track of expenses or managing assets; (5) taking medications.

The rest of the paper proceeds as follows. Section 2 includes a review of literature and Section 3 is a description of the data. In Section 4, I briefly present the model and show the main results in Section 5. Section 6 is the robustness tests and I conclude in Section 7.

6.2 Literature Review

Motivated by the significant negative effects of birth order on educational attainment, some recent studies have attempted to figure out the underlying causal mechanisms to account these effects. Firstly, a parent has limited quality time. First born children receive all the attention and quality time from their parents, while later-born children have to share their parents' time with their other siblings, especially when the age gaps between nearby siblings are small. Price (2008) finds that first born children receive more parent-child quality time than second-born children by using American Time Use Survey.

Secondly, later-born children are more likely to experience family disruption which may have significant effects on their mental health and later achievements (Hotz and Pantano 2015). In addition, Hotz & Pantano (2015) provide another channel of how birth order affects educational attainment by using National Longitudinal Study of Youth-Child supplement (NLSY-C). They find that the children's declining school performance is consistent with the extent of stringency in their parents' disciplinary restrictions. The parents also tend to be less likely to "punish" the later-born children when they receive low grades compared with the earlier-born children.

Thirdly, Lehmann et al. (2016) and Black, Deverux, & Salvanes (2016) find that mothers are more likely to quit smoking and to breast-fed their first born children by using National Longitudinal Survey of Youth dataset and Norway register data, respectively.

Fourthly, in the context of some developing countries which have a strong son preference, the first born sons are much more likely to receive more of their parents attention and investment. In the case of China, there is a long standing tradition that parents invest more in their first born son and live with their first born son when they are older. On the other side of the coin, later-born children might benefit more from the experience their parents have had raising well behaved children (Hotz and Pantano (2015)).

As for the literature of birth order on health outcomes, I mainly focus on the studies from the medical and economic fields. Due to limitations of data availability, existing studies measuring birth order effects on health outcomes are mainly focused on mortality rates, height, weight, and some diseases, like hypertension, allergy and asthma, cancer and asperger's syndrome. Oleary et al. (1996) examine the birth order effect on adult's total or cause-specific mortality by using a sample of 1,162 individuals. They find that women born in the middle are more likely to die from causes of death compared to the first born children.[20] In a more recent paper, Modin (2002) uses 14,192 samples in Sweden during 1915-1929 and examine the birth order effects on mortality as well. They find that later-born children have a higher mortality risks compared to first born children, especially for women. Wang et al. (2007) studies the birth order effect on the risk of being overweight by using data from 7,959 junior high students in Japan and conclude that only girls have statistically significant effects on the risk of being overweight when compared to middle-born girls. Jelenkovic et al. (2013) find that birth order has negative effects on BMI, but they do not find statistically significant effects on blood pressure. In addition, Lundborg et al. (2014) explores the birth order effect on height using data from Sweden and find robust adverse effects on height. The most recent paper from Black et al. (2016) documents the effects of birth order on a range of health outcomes and health behaviors using register data from Norway. Unlike educational outcomes, they failed to find clear birth order effects on health outcomes.

[20] cardiovascular or cancer are two exceptions.

6.3 Data

This paper uses the recently released nationally representative survey, which focuses on elderly people in China – the China Health and Retirement Longitudinal Study (CHARLS). The CHARLS included interviews from about 10,000 households and 17,500 individuals who were aged 45 and older in 150 counties/districts in 2011. The survey included questions concerning demographics, family background, health status, biomarkers, work, income, consumption, and assets. These individuals are revisited every two years and the current available waves are 2011 and 2013. This study uses both the 2011 and 2013 waves and all regressions are weighted using the longitudinal weights provided by CHARLS.

I present summary statistics in Table 6.1. I construct birth order is constructed in the following way. CHARLS asks each respondent how many siblings that are both alive and dead. Then the respondents were asked questions about how many older brothers, younger brothers, older sisters, and younger sisters for both alive and dead siblings. I construct birth order by adding both alive and dead older siblings (brothers and sisters) together plus one.[21] I set the sibling size to 5 if the sibling size is greater than five and drop the individuals in the sample whose sibling size was larger than 10. The average sibling size is about 4.7, which suggests very high fertility rates.[22] The high fertility rate is mainly due to the government's population policy after 1949. According to the data collect from the United Nations, the average number of children for each woman in China is more than six in the 1950s and 1960s, except during the Chinese Famine years (1959-1961) when total fertility rates declined dramatically. The extremely high fertility rate during the 1950s and 1960s is mainly due to Mao's population policy, which is "the more population, the stronger of the nation." During that period, the government highly encouraged women to give birth to as many children as possible and no birth control in any way. The samples in this study

[21] The birth order is the number of total older siblings plus one. The older siblings include both alive and dead older brothers and older sisters.

[22] The sibling size is ranged from 1 to 17 in our original samples. Since the families who have more than seven children are very small. For the convenience, I set the sibling size equal to 7 for the families have more than seven children.

include cohorts between 1915 and 1966 and the primary samples are from the cohorts that are born between the 1950s and 1960s.

The advantage of this data is that I can control for appropriate variables to estimate reliable birth order effects on health outcomes. Besides sibling size, I also control for gender, birth year, parents' educational level, parents' age at birth, and whether the individual was born in a rural or urban area in China. I include year fixed effects to account for possible changes in different years.

The health outcome variables include self-reported health status (excellent, very good, good, poor, very poor). I construct the poor self-reported health status dummy as an individual who reports having poor or very poor health. I also include number of IADL and BMI in the estimation. In addition, I also estimate the birth order effect on mental health in this study.

Mental health is measured by ten emotional questions.[23] Each answer was measured in four scales: rarely, some or a little, occasionally, and most or all of the time. Each scale was scored from 0 to 3. The CES-D (Center for Epidemiological Studies Depression) is the total score for all ten questions.[24] In addition, I also include cognitive abilities. TICS is used to represent cognitive abilities and it is measured by using the awareness of date and number measurements together.[25]

6.4 Method

The difficulty in identifying the birth order effect on health outcomes lies in the fact that first born children are more likely to be from small family sizes, while later born children have a

[23] The questions include: bothered by things, trouble keeping mind, depressed, everything was an effort, fearful, restless, lonely, hopeful and happy.

[24] Since hopeful and happy are two positive emotions, I score these two in a reverse way, which is, most of the time = 0 points, occasionally = 1 points, some or a little = 2 point and rarely or none = 3.

[25] Awareness of dates is measured in the following way: Respondents are asked to tell today's date (year/month/date of the interview date), the day of the week, current season in telephone. They get credits by telling the correct information. For example, if year is correct, they obtain one credit. If the month is correct, they get one more credit. In addition, they also ask to calculate the substraction of 7 from 100 for up to 5 times.

Table 6.1: Summary Statistics

	Obs.	Mean	Std. Dev.	Min	Max
1st Child	15738	0.26	0.44	0	1
2nd Child	15738	0.26	0.44	0	1
3rd Child	15738	0.20	0.40	0	1
4th Child	15738	0.14	0.34	0	1
5th or more Child	15738	0.14	0.35	0	1
1 sibling	15738	0.08	0.27	0	1
2 sibling	15738	0.14	0.35	0	1
3 sibling	15738	0.21	0.40	0	1
4 sibling	15738	0.57	0.49	0	1
Poor Health	15492	0.26	0.44	0	1
BMI	12544	23.78	4.07	11	50
Number of IADL	15696	0.46	1.08	0	5
CES_D	14166	7.03	5.55	0	28
Tics	14743	6.88	2.74	0	10
Demographic controls					
Men	15734	0.48	0.50	0	1
Birth Year	15738	1950.76	10.68	1915	1966
Father Literacy	15208	0.21	0.41	0	1
Father Primary School	15208	0.10	0.30	0	1
Father Middle School	15208	0.07	0.26	0	1
Mother Literacy	15292	0.06	0.23	0	1
Mother Primary School	15292	0.06	0.25	0	1
Age of Mother at Birth	13529	29.43	8.30	14	55
Age of Father at Birth	13250	32.39	9.10	14	65
Born in Rural Areas	15738	0.77	0.42	0	1

Note: All the samples come from the CHARLS 2011 wave and 2013 wave.

higher probability to be from large families. Although I control for family background information which include parents' age at birth, parents' educational level, children's gender, birth year, and birth place, there are still some omitted factors that may contaminate the results. For example, there may be a reason why the family decided to have two children rather than five children, which is something that I cannot control for using this dataset. Hence I group the samples by different sibling sizes to estimate the birth order effect on health. Specifically, I divide the samples into 2 children families and 5 or more children families. Table C.1 presents the number of observations for the different family sizes and the birth order. For example, one-child families only have 295 observations and are dropped in the estimation. A majority of the families in the sample have 4 or 5 children.

The basic regression equation in this study takes the following form:

$$H_{it} = \beta Birth\ Order_{it} + \gamma Sibling\ Size_{it} + \gamma X_{it} + \varphi_{birth\ county} + \theta_t + \varepsilon_{it} \qquad (1)$$

H_{it} stands for health outcomes for individual i in year t. β is the primary variable of interest which captures the birth order effect. I include a sibling size dummy to account for the effect of sibling size on the outcome variables. X_{it} includes individual level demographic and family background information: gender, birth year, father's education level, mother's education level, father's age at birth and mother's age at birth. Birth place (rural/urban) is included to account for the differences between rural and urban areas in China. Since the data does not allow us to control for family fixed effects, I try to minimize the estimation bias by controlling for birth county fixed effects.

Although I try to eliminate the omitted variables problem by using the above method, I suffer from having a small sample size and large standard errors as illustrated in Table 6.2. I further follow Ejmaes and Portner (2004) and Booth and Kee (2009) by constructing a relative birth order variable and a birth order index to solve this problem. Earlier studies that measure the birth order effect include both the birth order dummies and family sizes in the same equation to capture the birth order effect. However, since birth order and family sizes are related to each other, by including both of these variables in the same regression we cannot obtain accurate birth order effects. Using the relative birth order and birth order index can dramatically reduce the correlation between birth order and family sizes. In particular, the correlation of birth order and sibling size is 0.4873 in the CHARLS samples, but the correlation of the relative birth order and birth order index dropped to 0.24 which is half of the correlation between absolute birth order and sibling size. Particularly, the birth order index is constructed by using the absolute birth order divided by the average birth order.[26] And the relative birth order which is derived from Ejmaes and Portner (2004) is equal to (absolute birth order -1) /(total number of children -1).

I estimate the following model:

$$H_{it} = \beta B_{it} + \gamma X_{it} + \theta N_i + \varepsilon \qquad (2)$$

Similarly, H_{it} stands for health outcomes and X_{it} stands for demographic control variables. N_i is the total number of siblings and B_{it} is the new birth order index or the relative birth order.

6.5 Results

6.5.1 Birth Order Effects on Health for Different Family Sizes

Table 6.2 presents regression estimates using the specification discussed in equation (1). I divide the samples by different sibling sizes, from 2 children families to 5 or over children families. Table 6.2 contains three panels. The first panel presents the results for the whole sample, and the other two panels present the results for males and females, respectively. I focus on the first panel – the whole sample, in this part and discuss the gender differences later.

The results for health outcomes are shown from Table 6.2 to Table 6.6. The poor self reported health status in Table 6.2 is defined as individuals who report having poor or very poor overall health status. I find statistically significant birth order effects on poor health in the small family sizes, i.e. 2 or 3 children families. In particular, in the families with 2 children, the second born

[26] The average birth order is equal to half of the total number of children (N) plus one, i.e,, (N+1)/2.

Table 6.2: The Birth Order Effect on Poor Health

		Whole Sample		
Birth order	2-Children	3-Children	4-Children	5+-Children
2nd	0.069*	0.096***	0.033	-0.024
	[0.037]	[0.031]	[0.030]	[0.019]
3rd		0.118**	-0.016	-0.027
		[0.046]	[0.030]	[0.020]
4th			0.081*	-0.006
			[0.043]	[0.027]
5th				-0.003
				[0.022]
Observations	861	1,643	2,508	7,036
		Men		
Birth order	2-Children	3-Children	4-Children	5+-Children
2nd	0.085*	0.111**	0.031	-0.055*
	[0.048]	[0.043]	[0.038]	[0.029]
3rd		0.110*	-0.001	-0.032
		[0.065]	[0.038]	[0.029]
4th			0.093	-0.006
			[0.058]	[0.036]
5th				0.011
				[0.034]
Observations	495	841	1,258	3,387
		Women		
Birth order	2-Children	3-Children	4-Children	5+-Children
2nd	0.056	0.080*	0.041	0.01
	[0.065]	[0.043]	[0.043]	[0.026]
3rd		0.124**	-0.021	-0.021
		[0.058]	[0.049]	[0.028]
4th			0.068	-0.006
			[0.062]	[0.040]
5th				-0.017
				[0.031]
Observations	366	802	1,250	3,649

Note: *significant at the 10% level; **significant at the 5% level; ***significant at the 1% level. All the regressions have controlled for sibling size and the demographic background variables shown in Table 6.1. The regressions controlled for birth county dummies and year fixed effects. The standard errors are clustered at the birth county level.

children have a 7 percentage point higher probability of being in poor health relative to first born children. In the families with 3 children, the second born children and third born have about a 10-12 percentage point higher probability of having poor health compared to the first born child. The estimates from larger family sizes are not statistically significant.

In Table 6.3 I present the birth order estimates on the number of IADL. In general, there is no strong birth order effect on the number of IADL. Only in the 4 children families, the second born and third born have about 0.14-0.15 more number of IADL (30 percent to 33 percent to the mean) compared with the first born children. When looking at other family sizes, there are no statistically significant birth order effects of the number of IADL. In Table 6.4 I display the birth order effect on BMI and Table 6.5 the birth order effect on mental health problems. Both of them are not statistically significant for all family types. I further estimate the birth order effect on TICS in Table 6.6. The results suggest that in large families, later born children perform worse in terms of cognition, however the magnitude is not very large. In particular, in families with 5 or more children, the second born, third born, and fourth born have about 0.25 to 0.31 less number of TICS. As shown in Table 6.1, the mean of TICS is 6.88, so this accounts to 3.6 percent to 4.5 percent decrease.

Taken as a whole, the results in the first panel of Table 6.2 to Table 6.6 suggest that later born children tend to have worse overall health outcomes compared to first born children. However, this result is only seen in particular types of families and the magnitudes are economically small. We cannot conclude that first born children have an absolute advantage in health outcomes based on the above estimation.

6.5.2 Heterogeneity

In this session, I further explore the heterogeneous birth order effect on health outcomes by gender. I mainly focus on interpreting the results in the second panel (Men) and the third panel (Women) from Table 6.2 to Table 6.6. In Table 6.2, similarly to the whole sample results, later

Table 6.3: The Birth Order Effects on Number of IADL

Whole Sample				
Birth order	2-Children	3-Children	4-Children	5+-Children
2nd	0.027	0.087	0.140**	0.043
	[0.126]	[0.089]	[0.068]	[0.045]
3rd		-0.011	0.150*	0.029
		[0.072]	[0.080]	[0.044]
4th			0.132	0.013
			[0.084]	[0.058]
5th				-0.009
				[0.047]
Observations	872	1,669	2,535	7,107
Men				
Birth order	2-Children	3-Children	4-Children	5+-Children
2nd	0.026	0.245**	0.217**	0.019
	[0.113]	[0.104]	[0.096]	[0.061]
3rd		0.056	0.303***	0.051
		[0.086]	[0.113]	[0.066]
4th			0.257**	0.045
			[0.112]	[0.078]
5th				0.017
				[0.063]
Observations	502	850	1,271	3,418
Women				
Birth order	2-Children	3-Children	4-Children	5+-Children
2nd	0.108	0.014	0.098	0.071
	[0.268]	[0.121]	[0.099]	[0.066]
3rd		-0.009	0.043	0.012
		[0.108]	[0.131]	[0.072]
4th			0.034	-0.019
			[0.134]	[0.086]
5th				-0.029
				[0.075]
Observations	370	819	1,264	3,689

Note: *significant at the 10% level; **significant at the 5% level; ***significant at the 1% level. All the regressions have controlled for sibling size and the demographic background variables shown in Table 6.1. The regressions controlled for birth county dummies and year fixed effects. The standard errors are clustered at birth county level.

Table 6.4: The Birth Order Effects on BMI

		Whole Sample		
Birth order	2-Children	3-Children	4-Children	5+-Children
2nd	-0.125	-0.129	0.118	0.046
	[0.369]	[0.334]	[0.303]	[0.230]
3rd		-0.468	-0.115	0.082
		[0.397]	[0.328]	[0.233]
4th			0.044	-0.082
			[0.382]	[0.244]
5th				-0.334
				[0.240]
Observations	698	1,365	2,039	5,760
		Men		
Birth order	2-Children	3-Children	4-Children	5+-Children
2nd	-0.067	-0.098	0.513	-0.154
	[0.427]	[0.414]	[0.478]	[0.256]
3rd		-0.611	0.199	0.007
		[0.491]	[0.433]	[0.268]
4th			0.404	-0.044
			[0.476]	[0.324]
5th				-0.496
				[0.319]
Observations	406	706	1,037	2,792
		Women		
Birth order	2-Children	3-Children	4-Children	5+-Children
2nd	-0.072	0.026	-0.237	0.238
	[0.709]	[0.471]	[0.404]	[0.359]
3rd		0.077	-0.443	0.184
		[0.536]	[0.520]	[0.358]
4th			-0.299	-0.118
			[0.591]	[0.356]
5th				-0.139
				[0.331]
Observations	292	659	1,002	2,968

Note: *significant at the 10% level; **significant at the 5% level; ***significant at the 1% level. All the regressions have controlled for sibling size and the demographic background variables shown in Table 6.1. The regressions controlled for birth county dummies and year fixed effects. The standard errors are clustered at birth county level.

Table 6.5: The Birth Order Effects on CES-D

Whole Sample				
Birth order	2-Children	3-Children	4-Children	5+-Children
2nd	-0.074	0.176	-0.153	0.285
	[0.447]	[0.447]	[0.442]	[0.334]
3rd		-0.124	0.034	0.41
		[0.493]	[0.544]	[0.348]
4th			-0.78	-0.027
			[0.483]	[0.372]
5th				0.405
				[0.383]
Observations	764	1,492	2,319	6,543
Men				
Birth order	2-Children	3-Children	4-Children	5+-Children
2nd	-0.111	0.736	-0.338	0.571
	[0.575]	[0.488]	[0.461]	[0.494]
3rd		0.69	0.324	0.936*
		[0.622]	[0.516]	[0.481]
4th			-0.742	0.752
			[0.547]	[0.540]
5th				1.309**
				[0.576]
Observations	452	784	1,186	3,192
Women				
Birth order	2-Children	3-Children	4-Children	5+-Children
2nd	0.05	-0.161	0.14	0.055
	[0.861]	[0.742]	[0.703]	[0.426]
3rd		-0.816	-0.151	-0.099
		[0.717]	[0.881]	[0.442]
4th			-0.601	-0.779*
			[0.798]	[0.457]
5th				-0.495
				[0.477]
Observations	312	708	1,133	3,351

Note: *significant at the 10% level; **significant at the 5% level; ***significant at the 1% level. All the regressions have controlled for sibling size and the demographic background variables shown in Table 6.1. The regressions controlled for birth county dummies and year fixed effects. The standard errors are clustered at birth county level.

Table 6.6: The Birth Order Effects on TICS

Whole Sample				
Birth order	2-Children	3-Children	4-Children	5+-Children
2nd	-0.12	-0.086	0.002	-0.247**
	[0.234]	[0.258]	[0.167]	[0.106]
3rd		-0.003	-0.390*	-0.246*
		[0.226]	[0.223]	[0.127]
4th			0.056	-0.312**
			[0.186]	[0.146]
5th				-0.131
				[0.143]
Observations	805	1,557	2,412	6,785
Men				
Birth order	2-Children	3-Children	4-Children	5+-Children
2nd	-0.218	-0.258	0.029	-0.21
	[0.279]	[0.271]	[0.234]	[0.134]
3rd		0.123	-0.660***	-0.405**
		[0.280]	[0.249]	[0.182]
4th			-0.042	-0.706***
			[0.232]	[0.210]
5th				-0.420*
				[0.216]
Observations	473	811	1,223	3,297
Women				
Birth order	2-Children	3-Children	4-Children	5+-Children
2nd	-0.197	-0.163	-0.1	-0.362**
	[0.344]	[0.317]	[0.216]	[0.163]
3rd		-0.449	-0.027	-0.131
		[0.292]	[0.286]	[0.175]
4th			0.038	0.017
			[0.291]	[0.196]
5th				0.135
				[0.182]
Observations	332	746	1,189	3,488

Note: *significant at the 10% level; **significant at the 5% level; ***significant at the 1% level. All the regressions have controlled for sibling size and the demographic background variables shown in Table 6.1. The regressions controlled for birth county dummies and year fixed effects. The standard errors are clustered at birth county level.

born sons tend to have worse overall health outcomes when compared to the first born son and these results are only significant for small families of 2 or 3 children. For example, the second born sons have a 9 percentage point higher chance of being in poor health compared to first born sons in two children families. Moreover, first born sons have about an 11 percentage point less chance of being in poor health when compared to the second born and third born children.

Turning to the results in Table 6.3, results show some birth order effects for men in three and four children families. In general, later born sons have more number of IADL. For example, in four children families, the second born to fourth born sons have 0.2 to 0.3 more number of IADL (43.5 percent to 65 percent to the mean) compared with the first born son. As shown in Table 6.4, there are no statistically significant effects for both men and women. As for the mental health outcomes presented in Table 6.5, later born sons tend to have a larger depression scale than first born sons in large families. In families with 5 or more children, the third born and fifth born sons tend to have a 0.9 to 1.3 higher value on the CES-D scale. In the second panel of Table 6.6, I investigate the birth order effects on TICS for men and find some birth order effects in large families on TICS for men. Particularly, in families with 5 or more children, third born to fifth born sons have 0.4 to 0.7 less number of TICS compared with the first born son. These magnitudes are not large as well. When we look at the birth order effect for women from Table 6.2 to Table 6.6, there is little evidence of birth order effects except on the poor health status variable. Only in small families – 3 children families, the second born and third born girls have a higher probability of being in poor health compared to the first born girl.

In conclusion, birth order effects only exist for men, not for women. This result is expected due to the cultural preference for sons, especially for first born sons in China. Parents devote most of their resources to their first born son and the first born son usually inherits the family business, so it is not surprising to find that first born sons have better health compared to later born sons.

6.6 Robustness Checks

As shown in the above tables, I run all regressions by different family sizes, where I control for the omitted family background information. However, I also need to deal with the small sample size problem. To solve the small sample size problem, following Booth and Kee (2009) and Ejmaes and Portner (2004), I generate a birth order index and a relative birth order variable to solve this.

In Table 6.7 I present the results that use the birth order index from Booth and Kee (2009) and Table 6.8 has the results when I use relative birth order from Ejmaes and Portner (2004). These two tables generate very similar results. The probability of being in poor health status increases with the increasing order of birth. In addition, as the birth order increases, BMI tends to decrease. This is plausible due to the fact that in developing countries, especially in earlier decades when living conditions were extremely tough, decreased BMI meant larger probability of being undernourished. In this sense, later born children tend to have smaller BMI implying that later born children are more likely to be undernourished on average compared with the first born children.

In Columns 2 and 3 of Table 6.7, I present the result of the birth order effect on health by gender. Similar to the trend found in earlier tables, I find that first born sons have some advantage in all of the health indicators that I measured, while there are no birth order effects found for women. Specifically, first born sons have a lower probability of being in poor health and lower IADL compared to later born sons. In addition, later born sons have smaller BMI, higher depression scale values, and smaller cognitive abilities relative to first born sons. In Table 6.8, I use the relative birth order followed by in Ejmaes and Portner (2004) and the results are very consistent with the results found in Table 6.7: first born children have better overall health outcomes and a larger BMI compared with the later born children. In terms of all measured health outcomes, first born sons display an overall better health performance.

Table 6.7: Birth Order Index (Booth and Kee 2009)

	Column 1	Column 2	Column 3
	Whole sample	Men	Women
Poor Health	0.039***	0.048**	0.03
	[0.015]	[0.021]	[0.019]
Observations	11,186	5,486	5,700
Number of IADL	0.022	0.056*	0.000
	[0.026]	[0.033]	[0.043]
Observations	12,182	6,041	6,141
BMI	-0.252**	-0.289*	-0.18
	[0.120]	[0.156]	[0.180]
Observations	9,163	4,535	4,628
CES_D	-0.041	0.422*	-0.480**
	[0.169]	[0.227]	[0.237]
Observations	10,353	5,162	5,191
Tics	-0.062	-0.217**	0.074
	[0.070]	[0.100]	[0.085]
Observations	11,558	5,804	5,754

Note: *significant at the 10% level; **significant at the 5% level; ***significant at the 1% level. All the regressions have controlled for sibling size and the demographic background variables shown in Table 6.1. The regressions controlled for birth county dummies and year fixed effects. The standard errors are clustered at birth county level.

Table 6.8: Relative Birth Order (Ejrnaes and Portner 2004)

	Whole sample	Men	Women
Poor Health	0.029**	0.039**	0.021
	[0.012]	[0.017]	[0.018]
Observations	12,047	5,981	6,066
Number of IADL	0.013	0.053*	-0.016
	[0.024]	[0.032]	[0.037]
Observations	11,310	5,539	5,771
BMI	-0.199*	-0.214	-0.157
	[0.114]	[0.143]	[0.177]
Observations	9,861	4,941	4,920
CES_D	-0.061	0.365*	-0.459**
	[0.159]	[0.216]	[0.219]
Observations	11,117	5,614	5,503
Tics	-0.066	-0.144	-0.014
	[0.074]	[0.106]	[0.088]
Observations	10,753	5,331	5,422

Note: *significant at the 10% level; **significant at the 5% level; ***significant at the 1% level. All the regressions have controlled for sibling size and the demographic background variables shown in Table 6.1. The regressions controlled for birth county dummies and year fixed effects. The standard errors are clustered at birth county level.

6.7 Conclusion

In this study, I document the birth order effect on health outcomes in China. Although there is a growing literature studying the birth order effect on health in medical and economic fields, there are few studies that look at the birth order effect in China because of the availability of the data and China's "One-Child" policy.

In this paper, I do not find strong birth order effects for first born children, although there is some evidence to show first born children tend to have an overall better health status, lower IADL, and better cognitive abilities. However, when I look at the results by gender, there is evidence to show that first born sons tend to have advantage on some of the health indicators that are measured in this study. This is reasonable due to the preference for sons, especially for first born sons in Chinese culture.

To solve the limited sample size problem, I further use the birth order index and a relative birth order which followed by Booth and Kee (2009) and Ejmaes and Portner (2004) to run all estimations. The results from these two measures reach the similar conclusion as the first method: first born children have a better health performance compared to their later born siblings in terms of overall health status and BMI. Moreover, first born sons have better health performance on most of the health outcomes in this study compared with the later born sons. However, first born girls do not have any health advantage compared with the later born girls.

Appendices

Appendix A

Appendix to Chapter 1

Table A.1: Sample Sizes by Year, Ages 25-55

Year	**Sample size**
2003	7166
2005	7168
2007	7210
2009	7405
2011	7253
2013	7336

Table A.2: Descriptive Statistics on County Populations from the Merged Data

Mean	99555
Standard Deviation	160419
10^{th} Percentile	7003
25^{th} Percentile	14976
50^{th} Percentile	35341
75^{th} Percentile	117498
90^{th} Percentile	227014

Appendix B

Appendix to Chapter 2

Table B.1: Birth Location of Samples

Birth Place	Female	Male	All
Where were you born?			
Sample place	0.29	0.78	0.52
Another village or neighborhood in county	0.57	0.14	0.37
Another County or City in province	0.11	0.06	0.09
Another province	0.03	0.02	0.02

Source: CHARLS 2011 and 2013 wave.

Appendix C

Appendix to Chapter 3

Table C.1: Distribution of Birth Order across Family Size

	Birth Order					
Family Size	Eldest	Second	Third	Fourth	Fifth	Observations
Only child	295					295
2-Children	564	676				1,240
3-children	755	789	695			2,239
4-children	914	868	754	692		3,228
5-children	1,879	1,786	1,706	1,471	2,189	9,031
Observations	4,407	4,119	3,155	2,163	2,189	16,033

Source: CHARLS wave 2011 and 2013.

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